Automatic Scoring of Segmental Wall Motion in Echocardiography Using Quantified Parametric Images

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Abstract

A new automatic regional wall motion scoring approach based on parametric imaging was provided.

Black and white (B/W) echocardiography sequences were summarized into amplitude and time parametric images using the parametric analysis of main motion (PAMM) with new constraints on the transition times between muscle and cavity. Then segmental wall motion amplitude and time indexes were computed. A total of 518 segments (37 patients) were analyzed: an absolute agreement of 66% and a relative agreement of 94% were obtained between the visual assessment of B/W cine loops and the automatic scoring. Moreover, the new constraints allowed the estimation of a more relevant mean contraction time which contributes in a better characterization of wall motion abnormalities. This new automatic scoring could provide promising results in the analysis of stress studies.

1. Introduction

Echocardiography is the most frequently used modality for the study of left ventricular wall motion abnormalities in ischemic heart. It is indeed used in emergency rooms and intensive care units. It allows the assessment of regional wall motion abnormalities at baseline and under stress.

The analysis of the myocardial segmental wall motion in routine is mostly based on visual interpretation of B/W cine images. The interpretation of these images is widely dependant on operator training and is subject to large variability [1].

To reduce this inter and intra-observers variability, quantitative methods have been developed. Some of these techniques were based on the myocardial border detection such a Color kinesis [2] method, which provides both the magnitude and the chronology of endocardial motion. Other techniques provide myocardial velocities and more recently, Strain Imaging techniques [3] which study myocardial deformation are proposed. However the evaluation of the provided help to diagnosis images remains mostly visual except some new indices recently described.

In this paper, a new automatic scoring process which operates on parametric images is described. It displays regional wall motion scores from the parametric images provided by the PAMM method [4]. The PAMM method compared with other previously developed parametric imaging methods summarizes both motion information and chronological information of the endocardial wall over a cardiac cycle in only two parametric images.

The developed method was applied to a series of echocardiographic studies and the obtained wall motion scores were compared with those provided by the visual assessment of the parametric images and the gold standard scores provided by the visual assessment of B/W cine loops.

2. Methods

2.1. Patients database

Data of thirty seven patients were acquired at the department of echocardiography at the European Hospital Georges Pompidou. For each study, two dimensional harmonic gray scale two-chamber and four-chamber sequences were selected.

Image sequences were acquired during standard examinations in order to be representative in term of pathology and image quality with the daily hospital acquisitions. No study was excluded.

One cardiac cycle was isolated by selecting the onset QRS complex and interpreted visually by two experienced readers and regional wall motion was scored in a four point scale (**1**: normal, **2**: hypokinetic, **3**: akinetic, **4**: dyskinetic). Segment with extremely bad quality were not classified and therefore scored **5**.

2.2. Signal modeling

The method of parametric analysis of main motion based on the model of the window function assumed a high contrast between the cavity and the myocardium, implying that they could be distinguished by two distinct signal intensity levels (Figure 1).

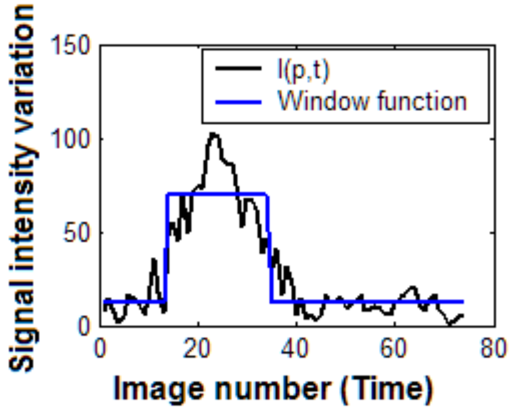

Figure 1: Real time-signal intensity curve and the associated window function

Considering these assumptions, the modeling of each time-signal intensity curve *I(p,t)* associated with the pixel *p* over a sequence of *T* images was given by equation 1 :

$$I(p,t) = A_B(p) + A_V(p).g(t, T_{ON}(p), T_{OFF}(p)) + e_I(p,t) \quad [1]$$

$$g(t, T_{ON}(p), T_{OFF}(p)) = \begin{cases} 1 & \text{if } T_{ON}(p) \le t \le T_{OFF}(p) \\ 0 & \text{otherwise} \end{cases} \quad [2]$$

The coefficient $A_B(p)$ was the baseline signal intensity, corresponding to end-diastole, the coefficient $A_V(p)$ was the variation of signal intensity, and g(t) was the window function, which depended on the two transition times $T_{ON}(p)$ and $T_{OFF}(p)$ between the baseline and the variable signal level. For pixels initially inside the cavity, close to the endocardial border, the transition times $T_{ON}(p)$ and $T_{OFF}(p)$ represented respectively the time of the beginning and the time of the end of the endocardial movement over the pixel p. Finally $e_I(p,t)$ was the residual error which must be minimized [4].

2.3. New physiopathological constraints

New constraints were imposed to the transition times T_{ON} and T_{OFF} to make the choice of the adapted window function more accurate. These constraints (equation 3) were based on the physiopathological knowledge of the cardiac cycle and linked with the durations of systolic and diastolic phases which we can define by the use of the time of the mitral valve opening (T_{MVOP}).

$$\begin{cases} T_{aq} < T_{ON}(p) < T_{MVOP} + 100 \\ T_{MVOP} - 100 < T_{OFF}(p) < 2 * T_{MVOP} \end{cases} \quad [3]$$

T_{aq} is the acquisition duration of one image. Times were expressed in *ms*.

T_{MOVP} was automatically estimated using the curve of a correlation coefficient between the end-diastolic image and the following images. This curve presents a shape similar to the curve of volume variation of the left ventricle during a cardiac cycle (Figure 2). T_{MVOP} was approximated by the minimum of the time corresponding to the minimum of the curve.

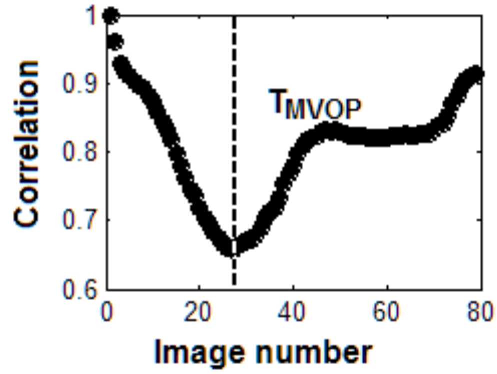

Figure 2: Correlation between the sequence images and the end-diastolic image.

2.4. Parametric images

The developed method summed up the information of the image sequence in four parametric images derived from the estimation, for each pixel, of the four parameters described above.

A_V and A_B amplitude images were color coded (green color for A_B , red color for the positive values of A_V and blue color for the negative values of A_V). Then, reading rules based on the position of color patterns and their width where then associated to this image.

Furthermore, the two images T_{ON} and T_{OFF} were combined into an image of mean contraction time called T_M ($T_M = (T_{ON}+T_{OFF})/2$). T_M was then normalized and was color coded according to the sign of A_V. The mean contraction time image provides chronological information, it is superimposed to the gray scale diastolic image to allow us distinguishing useful signal provided by walls motion from useless signal provided by papillary muscle motion or mitral valve motion.

The two images were interpreted simultaneously by the clinician.

2.5. New automatic scoring method

2.5.1. Useful geometrical knowledge

Images were segmented according to the left ventricular standard segmentation scheme (American Heart Association). The developed software proceeds from three points manually positioned on one chosen frame of the sequence (25% of the cardiac cycle). A clinician defines the apex (P1), the mitral annulus (P3, P2) and a distance *K*.

This segmentation is superimposed on both parametric images and gray scale cine loops when establishing the diagnosis.

To make the quantifying process less sensitive to the useless information a global mask around the left ventricle excluding the mitral valve was computed using the three points P1, P2, P3 and the distance *K* (Figure 3).

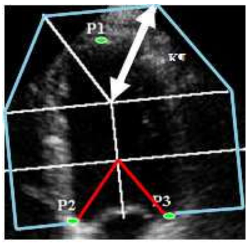

Figure 3: Points of interest and global mask.

2.5.2. Reliable motion information

The information contained in the amplitude image was organized into a hierarchy using the following processing steps:

A_B^N map was computed to provide the same meaning to the A_B parameters either if A_V is negative or positive.

$$\begin{cases} A_B^{\ N}(p) = A_B(p) & \text{if} \quad A_V(p) > 0 \\ A_B^{\ N}(p) = A_B(p) + \mathrm{A_V(p)} & \text{if} \quad A_V(p) < 0 \end{cases}$$

The weighting H map which defines the reliability of the motion information contained in the contraction relaxation parametric image A_V was computed (Figure 4):

$$\begin{cases} H(p) = 1 & \text{if} \quad 0 < \mathrm{A_B^{\ N}(p)} \le \mathrm{val} * |\mathrm{A_V(p)}| \\ H(p) = 2 & \text{if} \quad \mathrm{A_B^{\ N}(p)} > val * |\mathrm{A_V(p)}| \\ H(p) = 3 & \text{if} \quad \mathrm{A_B^{\ N}(p)} > 2 * val * |\mathrm{A_V(p)}| \end{cases}$$

Where $val = \frac{\max(A_B)}{\max(|A_V|)}$, is the segmental global contrast coefficient. The H map allows scaling the motion information according to the importance of its amplitude variation. The more relevant pixels were set to 1 in the H map.

2.5.3. Segmental quantitative indices of amplitude

First, a distance map *D* containing the Euclidian distance between pixel location and the long axis of the left ventricle was computed (Figure 4).

Then this distance map was combined with the three color image and the H map to estimate segmental profiles *Pr*:

$$\underset{1<d<K}{P_r(d)} = \frac{\left| N_R^{\ D(p)=d} - N_B^{\ D(p)=d} \right|}{\sum_{p\,/\,D(p)=d} H(p)}$$

Where N_R is the number of red pixels in the A_V map at the distance *d* and N_B is the number of blue pixels at the same distance *d*.

Finally, the segmental amplitude index IND_A was computed as the area under the red/blue profile situated before the maximal value of the green curve (Figure 4) (the area under the red curve is positive and the area under the blue one is negative).

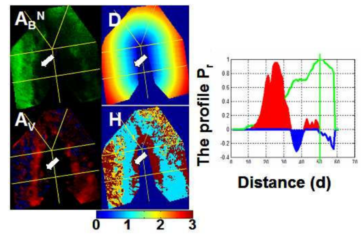

Figure 4: left: the parametric images A_B^N and A_V, the distance map D and the matrix H computed from A_B^N and AV. Right: the profile P_r (red/blue) estimated for the segment indicated by the arrow. The green curve is the normalized mean intensity in the A_B^N image according to the distance from the long axis.

2.5.4. Segmental mean contraction time

From the part of the T_M image corresponding to the pixels p with H(p)=1, the mean value of contraction times was computed for each segment.

3. Results

3.1. Reliability of the quantification process

The developed automatic scoring method aimed at synthesizing the information contained in the parametric images of amplitude and mean contraction time. It attempts to reproduce the results provided by the visual reading rules.

Three threshold values (S1= -1.2, S2=0.8, S3=3.4) were defined to convert the segmental amplitude indices IND_A into segmental wall motion scores. Furthermore, the segmental mean contraction time was integrated to reproduce in a reliable way the visual scoring of the mean contraction time image. Therefore, a segment is finally scored 2 if its amplitude score was 1 and its mean contraction time was greater than 500 ms and scored 3 if it was initially scored 2 by the amplitude indices and its mean contraction time was greater than 500 ms.

Wall motion scores were therefore obtained for the 518 segments of the data-base and then compared with those provided by the simultaneous visual analysis of the two parametric images. Thus, 72% of segments were scored similarly by both the visual and the automatic approaches and only (16 segments) 3% of segments were heavily misclassified (the difference between the two scores is greater than 1). Furthermore, 9 of the 16 heavily misclassified segments were basal.

3.2. Visual assessment of the B/W cine loops vs. visual and automatic assessment of parametric images

The visual scoring obtained from parametric images was compared with the visual scores provided by the interpretation of the gray scale native cine loops. 66% of the segments were scored similarly by the two methods and 4% of the segments (21 segments) were heavily misclassified. Among these segments, 7 were basal and 6 were apical.

Furthermore, the obtained automatic scores were compared with the visual assessment of the gray scale cine loops (Table 1). From this comparison, 66% of segments were similarly classified by the two approaches and (29 segments) 6% of segments are heavily misclassified. Among the heavily misclassified segments, 16 segments were basal segments and 4 were apical segments.

Visual scores from B/W cine loops (columns); Automatic scores from pramametric images (rows)

	1	2	3	4	5
1	256	63	7	4	0
2	40	63	29	8	2
3	4	9	15	5	0
4	2	4	1	6	0
5	0	0	0	0	0

Table 1 : contingency table between the visual assessment of the B/W cine loops and the automatic scoring.

Moreover, the defined constraints allow a better fit and therefore improve the quality of the parametric image of mean contraction time. Table 2 shows the *p* value of the means comparison using Student's test between the distributions of the mean contraction time parameter computed using PAMM with the simplified constraints and the new constraints according to visual wall motion scores established from B/W cine loops.

	1-2	1 -3	1-4	2-3	2-4	3-4
C	**4.10^{-3}**	**8.10^{-8}**	**8.10^{-7}**	**7.10^{-5}**	**5.10^{-4}**	**0,69**
N_C	**0.08**	**2.10^{-4}**	**6.10^{-3}**	**0.02**	**0.03**	**0.37**

Table 2: *p* value of the Student's test when comparing the new constrained PAMM version (C) with the previous version (N_C) in term of efficiency of the mean contraction time in the discrimination of wall motion abnormalities.

4. Discussion and conclusion

In this paper, the PAMM method is presented with new temporal constraints and a new automatic scoring process. In addition a mitral valve opening detection which showed a good agreement with the visual control on image sequences was provided.

Temporal constraints improve the power of the PAMM method, particularly the T_M image in term of wall motion abnormalities characterization (Table 2). Indeed, combining mean contraction times with the amplitude indices improves the automatic scoring: the absolute agreement with the visual assessment of the B/W cine loops increases from 64% to 66% and the heavily misclassified segments decreases by 17% (35 to 29 segments).

Furthermore, the new quantitative process based on the pixels counting corrected by the H map shows a higher performance in the automatic scoring than the method based on amplitude intensities [5]. Moreover, the new method does not require special processing according to the segment location. Indeed, it brings a better classification of apical segments. It reaches the performance of visual analysis of the parametric images.

In this study a promising and suitable tool to assess wall motion abnormalities is given. It is fast and requires limited manual intervention (the apex and the mitral annulus). Its application in stress and studies can be useful in myocardial viability and ischemia detection. It also can be helpful in asynchrony detection.

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