The Use of Different Measures of Signal Shape for Automatic Identification of Artefacts in Impedance Cardiography

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Abstract

The aim of this work was to find an easy and efficient method for automatic detection of artefacts in ICG signals. Form factors characterising the shape of the signal were selected because of the simplicity of implementation and the low computational cost. Different form factors were used to compare a single ICG heart cycle with a pattern and classify it as valid or artificial. The pattern was made by averaging 50 consecutive evolutions synchronized by the Q wave in an accompanying ECG signal. If the absolute difference between values of the same form factor calculated for the single evolution and for the pattern is lower than the cut-off point, it is recognized as valid; otherwise, it is marked as artefact.

The main objective of the study was to choose the most effective of the commonly-used form factors. Effectiveness was determined by using the area under the curve in receiver operating characteristic analysis. The necessary data were obtained by analysing the absolute difference between the values of the same form factor calculated for a single, manually classified evolution and for the pattern. We analysed cycles produced by 5 minutes of impedance cardiography observation in each of 20 subjects. The best efficiency was identified for the normalized standard deviation of the cycle from the pattern. In this case, area under the curve (AUC) was 0.86 and the cost-effective cut-off point was 56.76.

1. Introduction

The use of impedance cardiography (ICG) is still not widely applied in Holter-type monitoring. The main reason is the fact that ICG signal is about one hundred times weaker than ECG signal and more vulnerable to interference. There are many different types of artefacts in ICG signals, but the most difficult to detect automatically are those associated with temporary loss of connection between the skin and the application electrode. Conventional methods of artefacts removal, like band pass filtration [1-4], are not effective because the signal band overlaps with the noise band. Finding an effective method for automatic evaluation of a single heart cycle could increase the interest in ambulatory applications of ICG.

2. Material and methods

In this study, we used a new version of a previously described computer program that automatically identified characteristic points in the electrocardiographic (ECG) and impedance cardiography (ICG) signals [5, 6].

2.1. Pattern of ICG signal

The most significant improvement in the program involved the option of adapting the pattern (Fig. 1), which was recalculated every 1000 sequences (about 17min). It was created by averaging 50 consecutive cycles synchronized by the Q wave in the ECG signal.

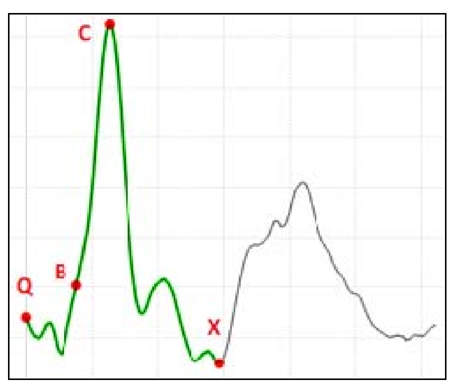

Figure 1. The pattern of the QQ cycle with characteristic points marked. B – where the curve crosses the baseline; C – the maximum for the segment; X – the minimum for the segment [5].

After automatic detection of characteristic points, the program calculates form factors (FF) and basic cardiac hemodynamic parameters: heart rate (HR), pre-ejection period (PEP), left ventricular ejection time (ET), stroke volume (SV), cardiac output (CO) and other, derivative ones.

2.2. Form factors used for evaluation of ICG signal

FF's, which are a quantitative method for evaluation of signals, allow one to obtain classification accuracy comparable to that of other, much more complex methods. They can be calculated for both 2D and 3D objects. Changes in each signal can be plotted as a function of time, and the curve thus produced may be treated as a 2D image. The undeniable advantages of these shape measures include their low computational cost and simplicity of implementation. The main problem is the fact that they must be selected individually depending on particular issues. There are no universal FF's, but some have more applications than others.

We discovered that in most cases, form factors describing QX segments give better results than those calculated for whole QQ segments. So far, many of the popular FF's were tested [7-9]. We present five which, in our opinion, have potential for further study.

Table 1. The definitions of the selected form factors.

$$FF_1 = \frac{GA}{LA}$$

$$FF_2 = \frac{L}{2\sqrt{nS}} - 1$$

$$FF_3 = \frac{SU}{SA}$$

$$FF_4 = \frac{\sum_{n=1}^{n} |x_{i+1} - x_i|}{n-1}$$

$$FF_5 = \sqrt{\frac{\sum_{n=1}^{n} (x_i - y_i)^2}{n-1}}$$

where:
GA – the number of samples having values greater than the average
LA – the number of samples having values less than the average
L – the circumference of the QX segment
S – the surface area relative to the average value for the QX segment
SU – the surface area with a value below the average of the QX segment
SA – the surface area with a value above the average value of the QX segment

The fourth factor (FF_4) is the average of the signal's rising speed (absolute value of the first derivative). The fifth factor (FF_5) is the standard deviation of the cycle from the pattern, normalized according to both the length of QX and the maximum amplitude of the dZ/dt signal.

2.3. Test data

As input data, twenty five-minute fragments of ICG signal were used (each from a different patient). Then, individual cycles were classified manually: artefact (1), normal (0). Comparing manual classification and absolute difference between the value of the same form factor calculated for the single evolution and for the pattern gave us enough information to plot the receiver operating characteristic (ROC). For this purpose, we used a MATLAB function created by Giuseppe Cardillo [10].

This function automatically draws the ROC curve and calculates the area under the curve (AUC) and the cost-effective cut-off point. The AUC is equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming "positive" ranks higher than "negative") [11]. The cost-effective cut-off is the point on the ROC curve the shortest distance from the upper left corner. It corresponds to the optimal cut-off value for the form factor.

For each optimal cut-off point, which was also the experimentally-determined tolerance for the FF, the confusion matrix and basic statistical parameters were designated. The statistical parameters are: sensitivity - TP/(TP+FN), specificity - TN/(TN+FP), positive predictive value - TP/(TP+FP) and negative predictive value - TN/(TN+FN).

3. Results

The collected information enabled comparison of the various form factors is presented in Table. 2 and Table 3

Table 2. Area under the curve (AUC) and the level of cost effective cut-off (CEC) for analysed form factors.

	FF_1	FF_2	FF_3	FF_4	FF_5
AUC	0.77	0.81	0.71	0.78	0.86
CEC	0.176	0.148	0.011	1.467	56.76

Table 3. Sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) for analysed form factors.

	FF_1	FF_2	FF_3	FF_4	FF_5
Sensitivity	71%	69%	64%	69%	79%
Specificity	73%	81%	68%	79%	78%
PPV	46%	54%	40%	52%	54%
NPV	88%	89%	85%	88%	92%

Figures 2–6 and tables 3–8 present the ROC curves and the confusion matrices, respectively, for each FF.

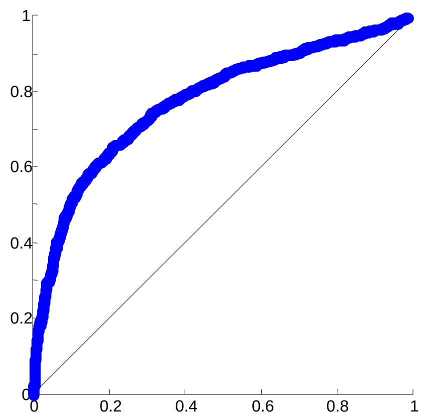

Figure 2. ROC curve for FF_1 (sensitivity v 1-specificity).

Table 4. Confusion matrix for FF_1.

		Manual	
		Artifact	Valid
Automatic	Artifact	1188 (TP)	1396 (FP)
	Valid	490 (FN)	3683 (TN)

Table 5. Confusion matrix for FF_2.

		Manual	
		Artifact	Valid
Automatic	Artifact	1159 (TP)	977 (FP)
	Valid	519 (FN)	4102 (TN)

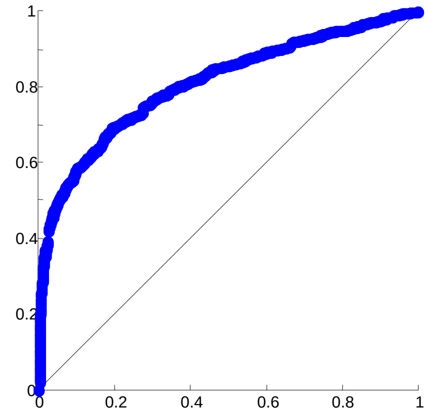

Figure 3. ROC curve for FF_2 also known as Malinowska's factor.

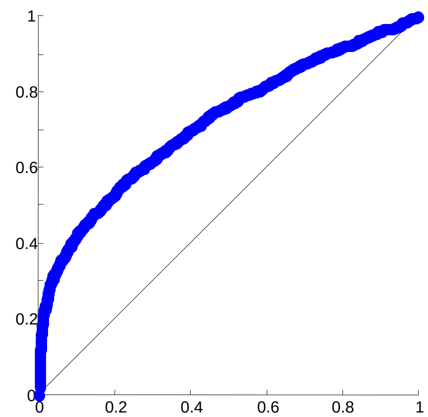

Figure 4. ROC curve for FF_3 (sensitivity v 1-specificity).

Table 6. Confusion matrix for FF_3.

		Manual	
		Artifact	Valid
Automatic	Artifact	1068 (TP)	1609 (FP)
	Valid	610 (FN)	3470 (TN)

Table 7. Confusion matrix for FF_4.

		Manual	
		Artifact	Valid
Automatic	Artifact	1155 (TP)	1083 (FP)
	Valid	523 (FN)	3996 (TN)

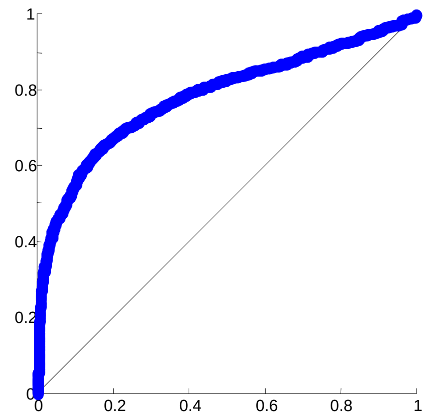

Figure 5. ROC curve for FF_4 (sensitivity v 1-specificity).

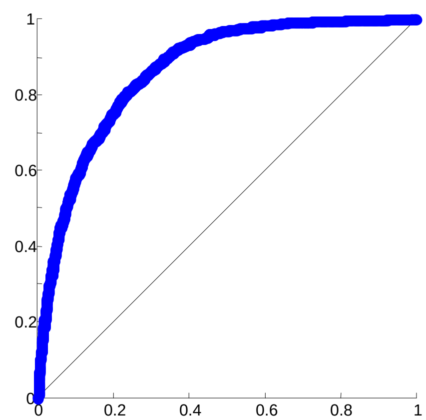

Figure 6. ROC curve for FF_5 (sensitivity v 1-specificity).

Table 8. Confusion matrix for FF_5.

		Manual	
		Artifact	Valid
Automatic	Artifact	1331 (TP)	1132 (FP)
	Valid	347 (FN)	3947 (TN)

4. Discussion and conclusions

It seems that the conclusion based on our preliminary results presented in a previous article [7] were too optimistic. Despite numerous attempts, none of the form factors reached a sensitivity of 80% or a specificity of 85%. On this basis, we can conclude that usage of only one of the tested FF's seems insufficient for automatic recognition of artefacts in ICG signal. On the other hand, using a combined criterion consisting of a few shape descriptors should improve the detection ability of the algorithm. Unfortunately, this would also increase the computational complexity of whole algorithm and raises new signal recognition problems.

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