Detecting "Strict" Left Bundle Branch Block from 12-lead Electrocardiogram using Support Vector Machine Classification and Derivative Analysis

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Abstract

Cardiac Resynchronization Therapy (CRT) is generally indicated for heart failure patients with a left bundle branch block (LBBB). "Strict" LBBB criteria have been proposed as a better predictor of benefit from CRT. Automatic detection of "strict" LBBB criteria may improve outcomes for heart failure patients by reducing high false positive rates in LBBB detection. This study proposes an algorithm to automatically detect "strict" LBBB, developed and tested using ECGs made available via the International Society of Computerized Electrocardiology (ISCE) LBBB initiative. The dataset consists of 12-lead Holter ECGs recorded before the therapy from the MADIT-CRT clinical trial.

The algorithm consists of multi-lead QRS complex detection using length transform, a support vector machine (SVM) classifier to identify QS- or rS- configurations and identification of mid-QRS notching and slurring by analyzing the variation of first and second derivatives of the signals respectively. The algorithm achieved an accuracy of 80%, sensitivity of 86%, specificity of 73%, positive predictive value (PPV) of 81% and negative predictive value of 79% on the training set. It achieved accuracy, sensitivity, specificity, PPV and NPV of 81%, 88%, 75%, 79% and 85% on the test set. High sensitivity to minor slurring and errors in QRS detection result in low specificity for LBBB detection.

1. Introduction

Left bundle branch block (LBBB) is the delayed conduction down the left bundle branch which results in delayed contraction of the left ventricle with respect to its right counterpart [1]. This condition leads to dilated cardiomyopathy and widened QRS. Restoration of the left ventricle synchrony is achieved by cardiac resynchronization therapy (CRT). Despite applying this device therapy in approximately 75000 patients per year in the United States, nearly one-third of the patients did not entirely benefit from this since these patients did likely not comply with the requirements of a true LBBB [2]. Hence, "strict" LBBB criteria have been proposed to improve LBBB detection to alleviate the false positive rate in LBBB detection and to improve the efficacy of CRT.

The "strict" LBBB criteria include QRS duration of 140 ms for male or 130 ms for female, QS- or rS- configurations in leads V1 and V2 and mid-QRS notching or slurring in 2 or more leads out of leads I, aVL, V1, V2, V5 and V6 [3]. Slurs/notches were required to have an onset after 40 ms and before 50% of the QRS width, relative to the onset of the global QRS complex.

This study proposes an algorithm, combining rule-based methods, machine learning and time-domain signal analysis to detect "strict" LBBB automatically. The algorithm also detects the onset and offset of notches and slurs which is vital for "strict" LBBB detection.

2. Methodology

2.1. Experimental Dataset

Data from the International Society of Computerized Electrocardiology (ISCE), LBBB initiative were used in this study [2, 4] with corrected adjudicated criteria [4]. The dataset consists of 12-lead ECGs sampled at 1 kHz with an amplitude resolution of 3.75 µV, recorded before CRT using Holter recorders with Mason-Likar lead placement, randomly divided into a training set with 300 records and a test set with 302 records. For each subject, the dataset contained 10 s ECG signal and a median beat derived from it. For this study, the median beat was used and was smoothed using a Savitzky-Golay filter of polynomial order 3 and frame length of 15.

The algorithm consists of three components: QRS complex detection, QS- or rS- configuration detection and notching/slurring detection. Output of these three components were combined per the "strict" LBBB criteria, to predict presence of LBBB. All signal processing and algorithm development was done in MATLAB (Release 2017b, The MathWorks, Inc., Natick, Massachusetts, United States).
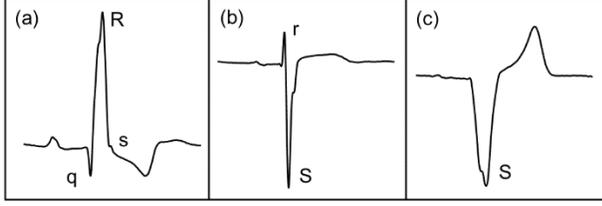
Figure 1. Example QRS morphology on the ECG lead V1 when (a) QS- configuration or rS- configuration are absent, (b) rS- configuration with small R wave followed by deep S wave and (c) QS- configuration characterized by a deep S wave.

2.2. QRS Detection

QRS complex detection was performed using length transform [5] which facilitated multi-lead QRS detection using median beats from all 12 leads. Multi-channel length transform was calculated using equation (1) where $x_j(t)$ is the median beat of the jth ECG lead, with a window size (w) of 70 and a global threshold of 1700. Global threshold was selected to minimize the mean square error between annotated onset and calculated onset (QRS_{on}) and annotated width and calculated width (QRS_w) on the training set. The resulting QRS_{on} and QRS_w estimates the global QRS onset and global QRS duration for the 12-lead median ECG beat.

$$L(w,t) = \int_{t}^{t+w} \sqrt{\sum_{j=1}^{12} \left(\frac{dx_j(t)}{dt}\right)^2} \qquad (1)$$

2.3. QS- or rS- Configuration Detection

"Strict" LBBB criteria dictate that either QS- or rS- configurations are present in both leads V1 and V2. QS- is characterized by a lone, deep negative wave whereas rS- is characterized by a small R wave followed by a deep S wave [6] (Figure 1). A support vector machine (SVM) classifier with radial basis function (RBF) [7] was trained to detect the presence of either of the configurations. The dataset for QS- or rS- detection was prepared using the extracted QRS complex in median beats from leads V1 and V2. Presence of either of the configurations was considered as positive class during training. The SVM classifier was trained using 75% of randomly selected training set data and was tested using the remaining 25% to obtain the best configuration with features: maximum/minimum amplitude, mean signal power and the signal entropy [8] of the QRS complex. Signal entropy (H) of QRS complex $y_k(t)$ where k ∈ leads {V1, V2} was calculated by generating the histogram of amplitudes with n number of bins of 100μV width where p_i is the frequency of occurrence of ith bin of amplitudes, followed by substitution to equation 2.

$$[p_1, p_2, \dots p_n] = hist\{y_k(t)\}$$

$$H = \sum_{i=1}^{n} p_i log_2 p_i \qquad (2)$$

2.4. Notching/Slurring Detection

Detection of mid-QRS notching in leads I, aVL, V1, V2, V5 and V6 was performed using the number of inflection points (M′) present during the QRS duration calculated in section 2.2. Inflection points were detected as the points where first derivative of the median beat crosses zero. When one or more notches are present, the number of zero-crossing points on the first derivative within the QRS complex is equal to or greater than 3 (Figure 2a). Therefore, the onset and offset of first notch corresponds to the 1st and 3rd inflection point, the onset and offset of second notch corresponds to the 3rd and 5th inflection point and so on.

During notching, the signal is not strictly increasing or decreasing. However, during slurring, the signal is either strictly increasing or decreasing with a distinct change of slope, which can be detected using zero-crossings in the second derivative (Figure 2b). Therefore, slurs were identified using the number of inflection points of the second derivative (M″) when notches are not present (M′ < 3), in a piecewise manner as shown in equation 3 where QRS_{on} and QRS_{off} are detected onset and offset of QRS complex and T is the time corresponding to inflection point. The onset and offset of the slurs were determined the same manner it was done for the notches, but with zero-crossing detection on second derivative.

$$[QRS_{on}, T_1] \ and \ [T_1, QRS_{off}] \quad for \quad M' = 1$$
$$[QRS_{on}, T_1] \ [T_1, T_2] \ and \ [T_2, QRS_{off}] \quad for \quad M' = 2 \quad (3)$$

Once the slurs and/or notches were detected, it was checked whether the onset satisfies the "strict" LBBB criteria by checking $QRS_{on} + 40 \leq t_{on} \leq QRS_{on} + QRS_w$ where t_{on} is the onset of notch or slur.
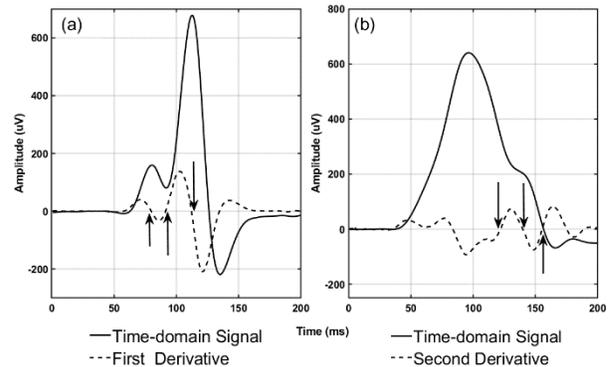

Figure 2. (a) First derivative of QRS complex on lead V1 during a notch, which satisfies notch criterion: number of inflection points (M′) equals 3. (b) Second derivative of QRS complex on lead V5 which satisfies slur criterion: number of inflection points (M″) equals 3.

2.4. Statistical Analysis

The "strict" LBBB detection performance of the algorithm and SVM classifier performance to detect QS- or rS- configuration were assessed using accuracy (Acc), sensitivity (Se), specificity (Sp), positive predictive value (PPV) and negative predictive value (NPV), as per equation 4 and confusion matrix (table 1) when presence of LBBB and presence of QS- or rS- configuration was considered as the positive class (+ve).

$$Acc = \frac{TP + TN}{Total} \quad Se = \frac{TN}{TP + FN} \quad Sp = \frac{TN}{TN + FP}$$
$$PPV = \frac{TP}{TP + FP} \quad NPV = \frac{TN}{TN + FN} \quad (4)$$

Table 1. Confusion matrix.

		Classified	
		+ve	**-ve**
Annotated	**+ve**	**TP**: No. of +ve's classified as +ve	**FN**: No. of +ve's classified as -ve
	-ve	**FP**: No. of +ve's classified as -ve	**TN**: No. of -ve's classified as -ve

The QRS detector performance was assessed using two metrics: difference between calculated onset and annotated onset (Δs) and difference between measured and annotated QRS width (Δd). The deviance from annotations was tested using one tailed t-test with null hypothesis: the difference is 0 with type I error set to 0.05. All statistical analysis was performed in Minitab® Statistical Software (Minitab 18, Minitab, Inc., State College, Pennsylvania, USA).

3. Results

The "strict" LBBB detection performance of the algorithm is summarized in table 2. The algorithm has similar performance metrics for initiative provided training and test datasets, which suggests that the rule-based approach is consistent. The algorithm performed well in terms of sensitivity but, relatively poorly on specificity due to false positives. However, the algorithm has good positive and negative predictive values on both datasets.

Table 2. LBBB detection performance.

Dataset	Performance (%)				
	Acc	Se	Sp	PPV	NPV
Training	80	86	73	81	79
Test	81	88	75	79	85

The performance of the SVM classifier used to detect QS- or rS- configurations is summarized on table 3. The specificity and NPV on the test set indicates that the classifier has falsely detected 16% of QS- or rS- configurations. On both datasets the QRS onset was detected early (Δs = -1.8 ± 8.9 ms, p = 0.001 on the training set, Δs = -1.3 ± 9.2 ms, p = 0.015 on the test set) and calculated QRS width was wider (Δd = 8.2 ± 18.0 ms, p < 0.0001 on the training set, Δd = 8.8 ± 19.0 ms, p < 0.0001 on test set). These results suggest that errors in QRS detection and QS- or rS- detection can directly contribute to high false positives in LBBB detection. Errors in QRS detection can indirectly contribute to false positive LBBB detection as well by affecting the slur detection.

Table 3. QS- or rS- configuration detection performance.

Dataset	Performance (%)				
	Acc	Se	Sp	PPV	NPV
Training	98	100	92	98	98
Test	96	98	84	97	89

4. Discussion

"Strict" criteria for LBBB have been proposed to better predict patient benefit from CRT therapy. This study presents an algorithm to automatically detect the presence of "strict" LBBB on 12 lead Holter ECGs. The algorithm analyses the median beat combining rule-based methods with machine learning. The algorithm has performed well on sensitivity but relatively poorly on specificity which elicits high false positives.

Errors caused by QRS onset detection and QRS duration calculation affect the LBBB detection when determining whether the onset of a slur/notch is within the specified region per "strict" criteria. For example, Figure 3 shows how a notch was missed due to late detection of QRS onset by 8 ms which caused the notch onset to be detected before 40 ms with respect to detected QRS onset and hence, do not comply with notch/slur onset criterion. In this scenario, the calculated notch onset deviated from the annotated onset only by 1 ms.

The slur detector is sensitive to minor slurring and/or artefacts which were not identified as slurs during annotation. The slur detector developed in this study adjudicated that the QRS complex contained a slur, if the
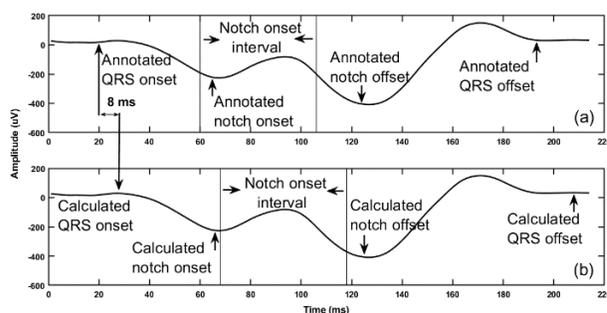

Figure 3. An example of a missed notch detection due to late detection of QRS. (a) Annotated QRS complex and notch (b) Detected QRS complex and notch, Δs = 8 ms and Δd = 16 ms, thus notch onset is out of bound.
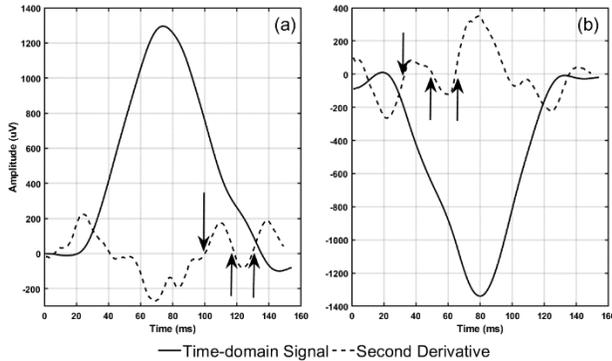
Figure 4. Examples of slur detection by algorithm: 3 zero-crossing points on second derivative of QRS complex (indicated with arrows) whereas (a) is annotated as a slur and (b) is not annotated as a slur and could resemble an artefact.

second derivative contained three zero-crossing points, regardless of how prominent the slur was (the degree to which slurring occurs) which is further explained in Figure 4. This compromised the specificity and the positive predictive value of the algorithm by falsely detecting slurs.

Even though the onset and offset of a notch could be clearly perceived, it is ambiguous and not clearly defined for a slur. In the literature, slurring is usually indicated as a point [9] rather than a duration with a clearly defined onset, but our algorithm detected onset and offset of slurring in an ad-hoc manner using zero-crossing points of the second derivative.

5.   Conclusion

We developed an automatic "strict" LBBB detection algorithm using the time domain behavior of the median beat, its first derivative and second derivative. The algorithm has performed well in identifying "strict" LBBB cases but has a considerable number of false positives. The algorithm detected wide QRS complexes early and QS- or rS- configurations falsely, which caused false positives. Improving QRS detection, QS- or rS- configuration and slur detection can further improve LBBB detection. More clear definition of slurs in terms of the onset and offset would facilitate such improvements.

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