Clustered Standard Deviation and its Benefit to Identify Atrial Fibrillation

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Abstract

Background: *Atrial fibrillation (AF) is a dysfunction of heart atriums shown as irregular heart activity leading to a higher risk of heart failure. Since AF may occur episodically, it is usually diagnosed using ECG Holter recordings. However, the presence of other pathologies and noise makes the automated processing of ECG Holter recordings complicated. Here, we present a new feature to distinguish AF from sinus rhythm as well as from other pathologies: Clustered Standard Deviation (C_{STD}).*

Method: *QRS complexes are extracted from the ECG signal, and inter-beat intervals (RR) are ordered by their length. Then, RR clusters are found and the mean RR value is computed for each RR cluster. C_{STD} is computed using a formula for standard deviation using cluster-specific mean values instead of a global mean.*

Results: *C_{STD} was evaluated for 7,254 ECG segments from a private dataset (MDT company, Brno, Czechia), 60 seconds length, 1-lead, 250 Hz sampling frequency. C_{STD} showed high values for AF while remaining low for other pathologies and sinus rhythm. C_{STD} between AF and other classes showed AUC 0.95. For comparison, a standard deviation of RR intervals leads to AUC 0.65 due to its sensitivity to other pathologies. Test on public MIT-AFDB dataset shown AUC and AUPRC 0.98 and 0.97, respectively.*

1. Introduction

The Atrial Fibrillation (AF) causes an irregular heart rhythm leading to a random distribution of QRS complexes. Regular P-wave is not present; instead, so-called f-waves are present in the whole ECG signal. In the past, several approaches to detect atrial fibrillation has been proposed, ranging from analysis of ventricular response [1]–[3] to more complex signal analysis [4] implementing machine-learning techniques including convolutional neural networks [5], [6]. Although this description might lead to the impression that detecting AF is already solved the issue, the CinC/Physionet Challenge 2017 [7] shown that this task is still challenging, especially under specific circumstances. Those specific circumstances mean cases when other pathologies must be expected in the ECG signal and/or the signal is collected from ECG holters during usual daily activities of patients; the usual daily activities result in a larger amount of noise caused by movement and its technical consequences as poor or broken contacts.

In this paper, we present novel descriptor sensitive to AF in one-lead ECG holter recordings.

2. Method

Here we present Clustered Standard Deviation (C_{STD}), which is a modification of standard deviation (STD). While STD works well for separation of AF and sinus rhythm (SR), it is insufficient when other pathologies are present (e.g., premature ventricular contractions – PVC – in bigeminy linking).

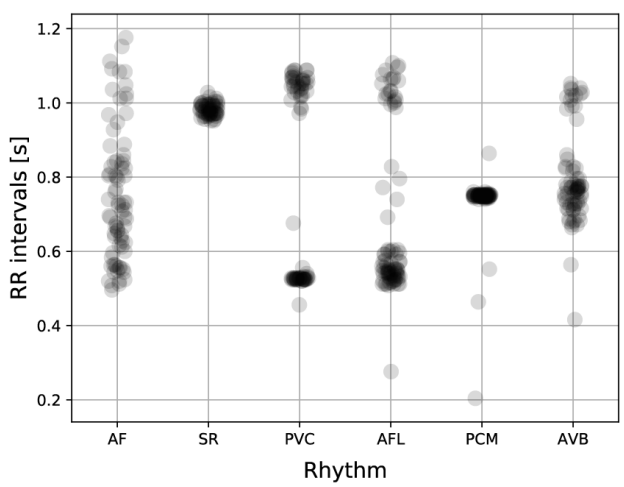

Figure 1. Examples of RR distributions in 60-second recordings of different rhythms. AF-Atrial Fibrillation, SR – sinus rhythm, PVC – premature ventricular contractions, AFL –atrial flutter, PCM – paced rhythm, AVB – 2nd degree AV block

Specific sign of AF is that QRS complexes are distributed in random; therefore, RR intervals do not produce clusters. Other pathologies, even if they show high STD, lead to some rhythm regularity – the mentioned PVC bigeminy will produce two clusters of RR intervals – short and long, as shown in Fig.1-PVC.

2.1. Clustered Standard Deviation

From the Fig.1 follows that if the STD is computed concerning RR clusters, then AF should still produce high values because it will form one (or more) wide clusters (Fig1-AF). Other pathologies and sinus rhythm (Fig1-SR) should provide low values since they can be clusterized into one or more tight clusters. Therefore, clustering of RR intervals is the key to the presented approach. The whole computational process is designed as follows:

First, QRS complexes are detected using a method based on envelograms [8], and inter-beat (RR) intervals are extracted.

Next, RR intervals are sorted by their value. Whenever a gap between neighboring (sorted) RR intervals is bigger then a limit L_G, a new RR cluster is defined. The limit L_G is computed as follows:

$$L_G = \max\left([a \times STD(RR), b\,]\right)$$

Optimal values of a and b coefficients were found later using the grid-search method using the whole dataset.

When RR intervals are clustered, the average RR interval A_c for each cluster c is computed. Finally, the C_{STD} is computed as follows:

$$C_{STD} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(RR_i - A_{ci})^2}$$

where N is the number of RR intervals, and the A_{ci} is an average RR of the cluster to which specific RR_i belongs.

2.2. Finding coefficients and evaluation

To observe C_{STD} behavior and to optimize limiting coefficients, we used private dataset (MDT company, Brno, Czech Republic). The dataset consisted of 123 one-hour, one-lead ECG recordings sampled at 250 Hz. These recordings were split into 7, 254 non-overlapping segments of length 60 seconds. Rhythms present in this private dataset are described in Tab. 1

Table 1. Description of rhythms in the private dataset

Rhythm	ECG Segments
Atrial fibrillation	1,062
Atrial flutter	649
Atrial tachycardia	649
AV-block	236
Premature atrial contractions	590
Premature ventricular contractions	1,063
Sinus rhythm	2,121
Noise	472

To maximize the C_{STD} capability to isolate AF, we needed to find proper values of limiting coefficients. Therefore, we used the grid-search approach and evaluated area under the curve (AUC) as well as area under the precision-recall curve (AUPRC). Since we found that C_{STD} can also be used to identify noisy recordings, we also run another grid search to find the best coefficients to isolate noisy recordings.

After the coefficients where optimized, we processed independent dataset MIT-AFDB [1] from PhysioNET [9] and evaluated the same AUC and AUPRC metrics. From the original 25 files, we excluded two due to missing data; finally, we extracted 13, 380 recodings (60 seconds long, containing only a single rhythm) using the WFDB-Python package [10]; the recordings extracted from the dataset are shown in Tab. 2

Table 2. Description of rhythms in the AFDB dataset

Rhythm	ECG segments
Atrial fibrillation	5,289
Atrial flutter	86
Sinus rhythm	8,005

3. Results

The grid search (to isolate AF) found limiting coefficients a = 0.05 [-] and b = 0.06 s. AUC and AUPRC on the private dataset shown 0.95 and 0.76, respectively. C_{STD} values for different rhythm are shown in Fig.2-top. Evaluation using the public AFDB dataset shown AUC and AUPRC 0.98 and 0.97, respectively.

For comparison purposes, we also evaluated a standard deviation (STD) of RR intervals (Fig2-bottom). Using STD shown AUC and AUPRC of 0.73 and 0.23, respectively.

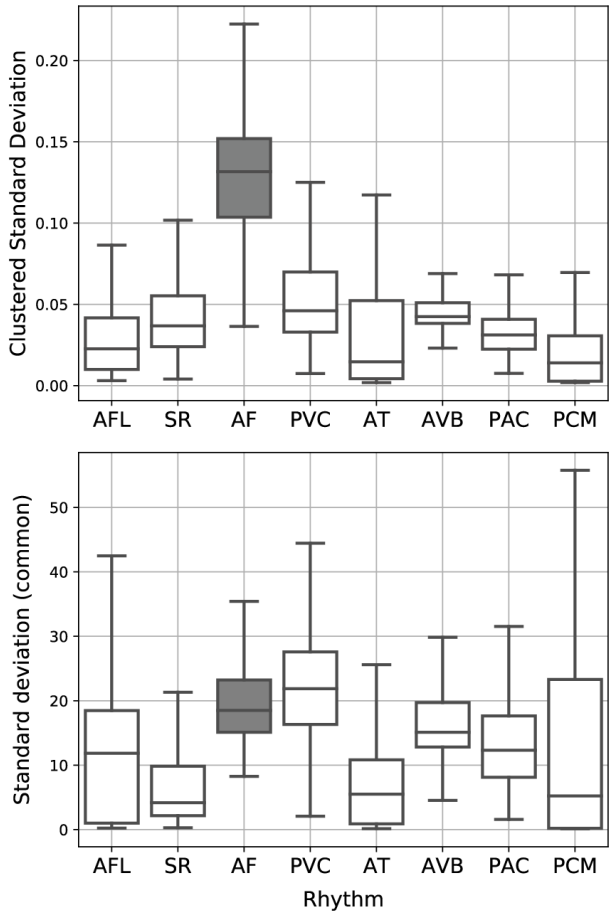

Figure 2. Comparison of the Clustered Standard Deviation (top) and the Standard Deviation (bottom) for different rhythms. Clustering limits were set to a=0.05 and b=0.06. Private dataset (MDT, Brno, CZ) consisting of 7, 254 ECG segments was used. AFL-Atrial flutter, SR – sinus rhythm, AF-Atrial Fibrillation (gray), PVC – premature ventricular contractions, AT – sinus tachycardia, AVB – 2nd degree AV block, PAC – premature atrial contractions, PCM – paced rhythm.

Another grid-search run to isolate noisy recordings shown a = 6 [-] and b = 0.04 s. This setting of C_{STD} coefficients shown strong ability to isolate noisy recordings with AUC and AUPRC 0.997 and 0.974, respectively (Fig.3).

Comparison of C_{STD} for AF versus sinus rhythm is shown in Fig. 4 for both the private and public dataset.

We also tested the C_{STD} for different sizes of input ECG signal varying from 5 to 60 seconds; the one-second step was used. Fig.5 shows method performance using the private dataset on shortened ECG segments. Limiting coefficients were set to *a=0.05* and *b=0.06*.

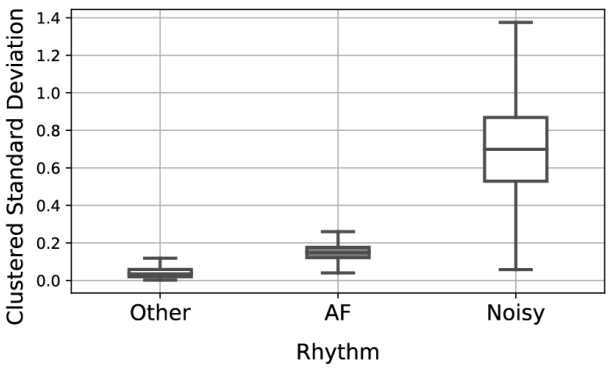

Figure 3. Clustered Standard Deviation could be used to detect noisy recordings if different clustering limits (a=6 and b=0.04) are applied.

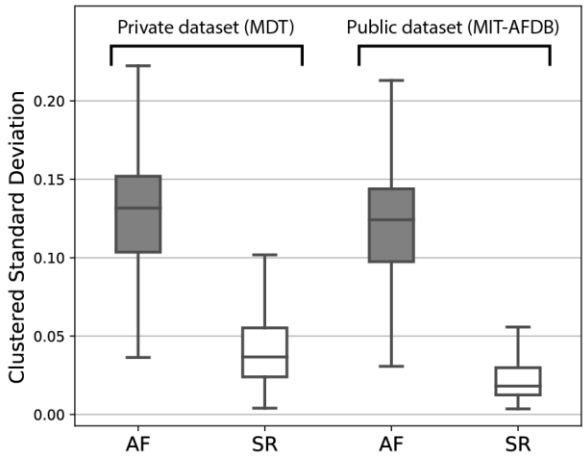

Figure 4. C_{STD} for atrial fibrillation (AF) and sinus rhythm (SR) for private (MDT) and public (AFDB) datasets

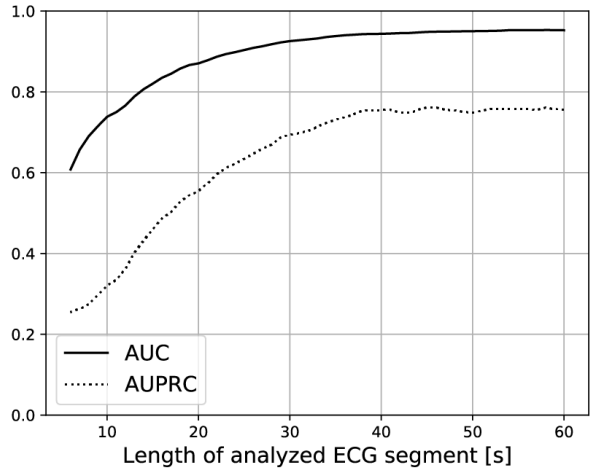

Figure 5. Method performance by the length of source ECG segment. AUC-area under the curve, AUPRC – area under the precision-recall curve. The performance was tested using 7,254 ECG segments from the private dataset.

4. Discussion

Presented results showed that the C_{STD} has strong potential for AF detection; and, furthermore, that the C_{STD} can separate AF from other pathologies as well. On the other hand, Fig.2 showed that even the best possible threshold for C_{STD} would result in some amount of false positives and negatives. Therefore, C_{STD} (for AF detection) should not be used alone, but in combination with other features as [11]. However, for comparison purposes we found a C_{STD} threshold at 0.081, producing the best F1-score for the private dataset. Then we computed the F1 score on AFDB dataset using the same threshold and compared it with existing methods (Tab.3). The performance of the C_{STD} is comparable to less complex models. The presented approach was not affected by the AFDB data; however, threshold retrained for AFDB would lead to F1 score of 0.93.

Table 3. Comparison to other methods - AFDB dataset.

Approach	F1 score
Corrected conditional Entropy [12]	0.85
This paper-C_{STD}	0.89
Markov model [1]	0.90
Convolutional neural networks [6]	0.99

Tests using different lengths of ECG segments (Fig. 5) reveals that the usability of C_{STD} decreases if shorter segments then 40 seconds are used, but further elaborating with limiting coefficients could help to reduce this loss.

In addition to our primary goal, results in figure 3 suggested that C_{STD} could be successfully used for the detection of noisy recordings, but it should be mentioned that these results will probably change when different QRS detection method is used (for example a method less sensitive to noise artifacts).

Finally, results from the independent AFDB dataset (Fig.4) shown the similar trend in C_{STD}; in SR from AFDB C_{STD} shown smaller variation probably reflecting the fact that AFDB files were recorded in the resting supine position while private MDT dataset was recorded during a common daily activity of patients.

5. Conclusion

We presented a novel feature to detect AF, the Clustered Standard Deviation. Using the private dataset we have shown that the feature is valuable especially if other rhythm disturbances are expected, which is a common case in holter ECG processing. Test on public AFDB dataset showed that C_{STD} works in the same manner with the independent data. In addition, we also showed that the presented method could be used to detect noisy recordings if different limiting coefficients are used.

Acknowledgments

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