Detection of Short Supraventricular Tachycardias in Single-lead ECGs Recorded using a Handheld Device

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Abstract

Short supraventricular tachycardias (S-SVTs) have been associated with a higher risk of developing atrial fibrillation (AF). Hence, identification of participants with such arrhythmias may increase the yield of AF screening over time. However, the lower signal quality of ECGs recorded using handheld screening devices and the abundance of aberrant ectopic beats and various arrhythmias in the elderly, who are the target population in AF screening, challenge the detection of S-SVT. In the present work, a new method for detection of S-SVT is presented, which in addition to rate and duration criteria, is based on the assumption that only subtle differences in beat morphology may occur during S-SVTs, as all beats are assumed to have the same origin. Therefore, any episode with a sequence of similar beat morphology is considered as an S-SVT candidate while any episode with different morphology due to signal disturbances or aberrant ectopic beats is excluded. For this purpose, a support vector machine (SVM) was trained and validated, using a simulated ECG database, to classify an episode as either consisting of beats of similar or non-similar morphologies. Episodes identified as S-SVT candidates are subject to two further rhythm criteria in order to confirm the presence of an S-SVT. The performance of the S-SVT detector is evaluated using a subset of the StrokeStop I database (305 S-SVT out of 8258), resulting in a sensitivity, specificity, and positive predictive value of 88.8%, 92.0%, and 29.9%, respectively. In conclusion, the results suggest that the proposed S-SVT detector has the potential to reduce the number of false S-SVT detection.

1. Introduction

Screening of AF, especially in the elderly population with the highest AF prevalence, provides the opportunity to identify patients with AF and initiate anticoagulation treatment to reduce the risk of stroke. While the usefulness of AF screening depends on successful identification of AF patients, its usefulness may be enhanced by identification also of participants at risk of developing AF.

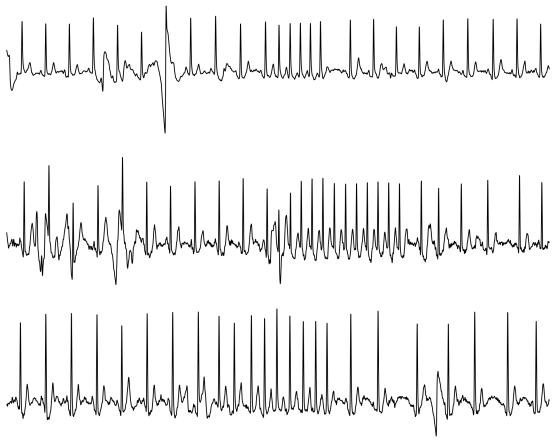

Figure 1. Three examples of ECGs recorded using a handheld device containing S-SVTs.

Several studies have demonstrated an increased risk of future AF for individuals with excessive supraventricular ectopic activity and atrial runs [1–4]. Short episodes of supraventricular arrhythmias have also been associated with a higher risk of developing AF in a 5-year follow-up study [5]. In [5], it was shown that different types of short supraventricular ectopies including isolated supraventricular ectopic beats, bigeminy, trigeminy, and short runs ($\geq$ 5s and $\leq$ 30s), were associated with a higher risk of AF development, with the highest risk for irregular runs without P waves. Such short runs, irrespective of irregularity and P wave presence are here referred to as *short supraventricular tachycardia/S-SVT* [5]. Specifically, an S-SVT is here defined as episodes with at least 5 supraventricular beats in $\leq$ 2400 ms [5].

The presence of S-SVT is also associated with an increased risk of undetected paroxysmal AF at the time of screening [6]. Therefore, the detection of S-SVT may en-

hance the usefulness of AF screening, e.g., by initiating more frequent screening for this patient group.

Mass-screening of AF is typically done by means of handheld devices, which are used outside the clinical setting, e.g., in the screening participants' home. Hence, the risk for noise and artifacts in the recorded ECGs are considerably higher when compared to, e.g., a resting ECG. In a previous work, its has been shown that identification of a small percentage of AF cases in a screening database results in a large manual review group of AF candidate signals [7] where the main content consists of falsely detected irregular rhythms caused by falsely detected QRS complexes, and correctly detected irregular but non-AF rhythms. The shorter events that are targeted for detection, the lower the positive predictive value will become.

In the present study, a two-stage approach for detection of S-SVT is presented. First, all sequences of beats with similar morphology are identified using an SVM, trained using simulated signals generated by the ECG simulator in [8]. The resulting episodes are subject to set of rhythm criteria defining an S-SVT episodes. The performance of the two-stage detector is evaluated using a subset of StrokeStop I that is expert annotated.

2. Databases

Two databases are used in the present study: a simulated ECG database (SIM-DB) and a subset of the StrokeStop I database (SSI-DB) [9].

The simulated ECG database is generated using the ECG simulator in [8], which accounts for a varying level of noise based on the MIT-BIH Noise Stress Test. A total of 18,000 30-s ECGs were generated using the following six noise levels: $30\mu V$, $60\mu V$, $90\mu V$, $300\mu V$, $600\mu V$, $900\mu V$. For each noise level, 3,000 ECGs were generated. Note that the simulated signals does not contain S-SVT episodes, as SIM-DB is only used to train the SVM for identification of episodes with similar beat morphology or non-similar beat morphologies, see Sec. 3.2.

The SSI-DB is a subset of the StrokeStop I database, which is expert annotated with regard to the presence of S-SVT. The SSI-DB contains 8258 recordings, of which 305 are annotated as ECGs containing S-SVT.

3. Methods

The proposed approach for detection of S-SVT consist of the following steps: First, preprocessing and QRS detection are performed. Next, sequences of consecutive beats with similar morphology within a recording are identified, and finally, these are subject to a set of rhythm criteria in order to confirm the presence of an S-SVT episode.

3.1. Preprocessing and QRS detection

To suppress baseline wander and unwanted high frequency content, a zero-phase 4-th order bandpass filter is applied to the ECG signals. QRS detection is performed using the built-in QRS detector in a commercial software (Cardiolund AB, Lund, Sweden).

3.2. Identification of similar beat sequence

After preprocessing and QRS detection, sequences of consecutive beats with similar morphology are identified. The shortest possible S-SVT in this work is set to five consecutive beats, and therefore a sliding window of 5 detections produced by the QRS detector is used. Identification of 5 consecutive beats with similar morphology is formulated as a binary classification problem, where a sequence is either classified as similar or non-similar morphologies. An SVM with a radial basis kernel is used as classifier.

Based on the sliding window, an interval of [-150, +150] ms around each detection produced by the QRS detector is extracted, resulting in a detection ensemble of size 5×300 samples. Next, a corresponding residual ensemble is defined, where a template within the detection ensemble is selected, and subtracted from the other detections. The template is selected as the beat detection resulting in the lowest mean absolute residual value after subtraction from the other beats. In this way, the most frequent morphology within the ensemble is subtracted from the rest.

Four features are extracted from the residual ensemble: The mean absolute value of the residuals, the mean of the standard deviation of the residuals, the interquartile range, and the difference between 99% and 1% percentiles. These features reflect when a residual is larger than normal, e.g., due to a ventricular ectopic beat or a falsely detected disturbance.

In order to train the SVM, episodes of 5 consecutive detections are selected from SIM-DB where the noise level could be controlled to cause falsely detected beats which are expected to have a deviating morphology. In order to label the training data, the ECGs in SIM-DB are subject to QRS detection, where these detections are compared to the QRS locations produced by the ECG simulator. If the QRS detections and reference locations match, i.e., ≤ 10 ms difference, the 5 consecutive beats are labeled as having a similar morphology, and when the difference is ≥ 75 ms, the episode is annotated as having non-similar morphologies. Note that to ensure that the QRS detections and annotations does not match due to concurrence of noise and artefacts with sharp noisy spikes, the similar morphology class is collected from the first three quality levels, i.e., 30 μV, 60 μV, and 90 μV.

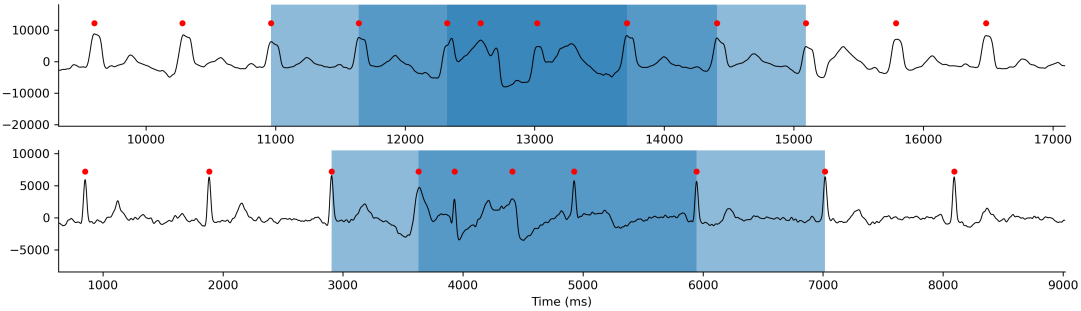

Figure 2. Two examples of ECGs with noise and artefacts, resulting in 5 detections in $\leq$ 2400 ms, which are identified using the SVM and excluded from further processing.

3.3. S-SVT rhythm criteria

After identification of sequences of 5 consecutive beats with similar morphology, these episodes are subject to two rhythm criteria. The first criterion is associated with the definition of S-SVT used in the present work, i.e., 5 consecutive beats appearing in $\leq$ 2400 ms. The next criterion accounts for the fact that such episodes should also in average display a significantly faster heart rate compared to the rest of the recording. Therefore, to be identified as an S-SVT, the median RR interval of the S-SVT should be at least 15% lower than the median RR interval of the remaining RR intervals within the 30-s recording but outside the S-SVT.

3.4. Performance evaluation

The performance of the proposed method is evaluated in the following two ways: First, only the similar beat sequence identification performance is investigated, and second, the entire S-SVT detection performance is analysed. The performance is assessed by means of sensitivity (Se), positive predictive value (PPV), and specificity (Sp), for both cases.

4. Results

To select the SVM hyperparameters, i.e., C and γ, 5-fold cross validation was performed for SIM-DB. The resulting Se, PPV, and Sp are 99.6, 99.4%, and 99.5%, respectively. The final SVM model is trained on the entire SIM-DB. Figure 2 shows two examples of recordings with 5 detections (including false detections due to noise) that appear within $\leq$ 2400 ms. When using the proposed step to assess the morphologic similarity of the detections, such episodes are excluded before the rhythm criteria are applied.

The trained S-SVT detector was applied to the SSI-DB to investigate its performance for the detection of S-SVTs. For this database, the resulting performance is shown in Table 1.

Table 1. S-SVT detection performance on SSI-DB

S-SVT detection performance	Se (%)	Sp (%)	PPV (%)
	88.8%	92.0	29.9

5. Discussion and conclusions

In the present work, a detector for S-SVT is introduced and its performance is evaluated using a subset of the StrokeStop I database. The proposed approach for the detection of S-SVT is based on the assumption that only a limited degree of morphologic variability is observed within such episodes.

In the present work, a simulated ECG database was used to create the two training categories of signals. While it may be possible to use the publicly available datasets with annotated beats to generate the training data, using a simulator provide control over the similarity of the beat morphologies.

The investigated problem could have been addressed using a signal quality assessment approach for exclusion of noisy segments combined with a heart beat classifier for identification and exclusion of aberrant ectopic beats. Here, the two mentioned stages are addressed using the SVM which identifies S-SVT candidate sequences that display similar beat morphology for further rhythm assessment. Notably, the proposed approach is independent of heart rate, rhythm regularity, and the individual heart beat morphology of the subjects, as only 300 ms around each detection is considered and as the proposed method only deals with differences between detections, i.e., residuals.

Future work is aimed at improving the presented approach and evaluate the performance on a larger AF screening database.

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