

# Automatic Screening of Atrial Fibrillation in Thumb-ECG Recordings

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## Abstract

*The present study proposes a novel sorting algorithm for identification of patients with atrial fibrillation in large one-lead ECG repositories. Repeated measurements at home with automatic transmission of data to a central database is presently tested in the search for atrial fibrillation for the long-term purpose to reduce the incidence of stroke. Such screening rapidly generates large databases of signals waiting to be sorted and prioritized. The one-lead ECGs were first preprocessed to remove baseline wander followed by beat detection and beat classification. A rhythm analysis stage was employed to perform RR interval analysis with negligible influence of ectopic beats and disturbances. RR interval information in combination with a waveform clustering procedure applied to the expected P wave intervals were used to sort the database into a low priority group containing mainly sinus rhythm, a high priority group containing all ECGs with irregular beat patterns, and a third group showing an unreliable RR series. The outcome of the algorithm was compared to an annotated database containing 2837 one-lead ECG recordings from 103 patients where each recording was visually inspected by a physician. The proposed method was able to divide the database into a low-priority group containing 93% (n=2357) of the sinus rhythm cases and a high priority group containing 98% (n=55) of the atrial fibrillation cases. In addition, 3.7% were found to have an unreliable RR series. In conclusion, automatic analysis of one-lead ECG databases can quickly guide the physician to find recordings with high probability to contain atrial fibrillation and can automatically indicate if a recording needs to be remade due to quality problems.*

## 1. Introduction

Atrial fibrillation (AF) is a cardiac arrhythmia characterized by uncoordinated atrial activation with consequent deterioration of atrial mechanical function and an irregular ventricular response. Atrial fibrillation is the most common arrhythmia in clinical practice with a prevalence of

0.4–1%, progressing to around 8 % for those above 80 years of age [1]. Atrial fibrillation constitutes a major risk factor for stroke and for mortality from other cardiovascular causes. An estimated 4.5 million people in the European Union (EU) have paroxysmal or persistent AF. Atrial fibrillation is an extremely expensive public health problem (approximately €3000 annually per patient); the total cost burden approaches €13.5 billion in the EU (2006) [1].

Treatment with oral anticoagulation drugs reduce the risk for stroke with more than 65% in patients with atrial fibrillation. Continuous screening for AF in the population above 75 years of age has therefore been suggested and is presently being evaluated. A remaining problem is, however, to find and diagnose the silent AF patients to a low cost. Recently, mobile phone based one-lead ECG devices have started to be used for screening and home surveillance of risk patients. In an ongoing research study in Sweden, 13000 75–76 year olds are presently screened using such one-lead ECG recorder from Zenicor ([www.zenicor.com](http://www.zenicor.com)) with an integrated mobile phone that automatically transmits the ECG to a database. The patient places his or her thumbs on the device twice daily or does so in the case of palpitations or symptoms suggestive of arrhythmia [2]. The use of this type of simplified ECG devices for use at home is likely to grow significantly not only among risk patients but also for continuous health monitoring in the entire population. Consequently, enormous and ever-growing databases of signals will be recorded and stored in different repositories waiting to be sorted and prioritized. In this work, we propose a sorting algorithm for such ECG repositories for the purpose of rapid and cost efficient sorting of data into low and high priority groups.

Detection of AF is standard in ECG equipment as well as in implantable defibrillators and cardiac monitors. The challenge in one-lead ECG recordings (lead I between the thumbs) is the often significant influence of rapid baseline wander which may disturb the beat detector which in turn may result in a complex RR series even when sinus rhythm is recorded. Other challenges is their often short duration and the fact that both the f/F-waves of atrial fibrillation/flutter and the P waves of normal rhythm are

weakly expressed in the thumb measurement corresponding to lead I. Thus, the AF detection for this type of recordings relies heavily on the preprocessing of the signal and the quality and postprocessing of the RR series.

The main objectives of the present study is to provide a method which can perform QRS detection in all thumb-ECG recordings independent of the signal quality and which can sort a large database of such ECGs into low and high priority and poor quality groups. In Secs. 2 and 3 respectively, the proposed method and the database used in the study are described. The results of the study are presented in Sec. 4 and in Sec. 5 the work is discussed. Finally, in Sec. 6, the main conclusions are given.

## 2. Method

The proposed method is divided into five analysis stages: preprocessing and beat detection, rhythm analysis, P wave detection, quality control, and finally, a rhythm sorting stage. Each of the analysis stages is described in the corresponding paragraph below.

### *Preprocessing and beat detection*

The one-lead ECGs were first preprocessed to remove offset, baseline wander, and powerline disturbances. In addition, baseline level estimation, beat range estimation and baseline correlation estimation were performed. Beat detection combined with crosscorrelation-based classification were employed so that beats with different morphologies were separated into different classes. If two beats were detected too close ( $RR < 300\text{ms}$ ), e.g., due to poor signal quality, the one deviating the most in terms of morphology from the main class was discarded from the RR series.

### *Rhythm analysis*

Based on the resulting RR series, rhythm analysis is performed by evaluating only RR intervals between consecutive beats with similar morphology. If two different groups of beat morphologies are frequently occurring (covering  $> 35\%$  of the beats each), both are used in the evaluation. The rhythm analysis stage evaluates the standard deviation of the resulting RR series ( $RR_{\text{std}}$ ), the percentage of RR intervals within an interval of  $\pm 60\text{ms}$  around the median value ( $RR_{\text{pm}60}$ ), filtered versions of the RR series revealing frequently occurring SVES or bigemini rhythms, the number of separated groups of RR intervals, and possible integer ratios in the RR series. The above procedure efficiently separates RR series affected by disturbances or occasional ectopic beats from irregular rhythms.

### *P wave detection*

In addition to rhythm analysis, P wave detection is performed both in the average beat of the main class and by applying waveform characterization to a generated signal

consisting of concatenated P wave intervals [3]. In the average beat, a ratio is calculated between the main peak in the P wave interval and the noise level in the entire average beat (PAVB) as described by the level of the local minima between the peaks in a rectified and smoothed version of the average beat. In the P wave waveform analysis, a period of 250ms before the QRS complex including a possible P wave is cut from all beats belonging to the main class and concatenated into a P wave signal. The repetitiveness and consistency in this signal is evaluated by modeling the signal as a fundamental (of 4 Hz) and a set of amplitude-scaled and phase-shifted harmonics describing the waveform of the signal. The modeling is performed in short blocks of 0.5 s duration and the amplitude scales and phase shifts of the harmonics of all blocks are clustered using the method in [3]. The following resulting parameters are used to establish a reliable P wave pattern verification: the P wave average model error (PAME), the part of the concatenated P wave signal having a low enough model error making it acceptable for clustering (PACC), the percentage of signal blocks represented by the largest waveform cluster (PCLU), and the strength of the largest waveform cluster (PSTR) describing how similar the included P waves are (between 0–1).

### *Quality control*

Quality control is achieved by analyzing how large part of the RR series that contains consecutive beats with similar beat morphologies (PSIM). If this part is less than 25%, the recording is marked as having an unreliable RR series not suitable for automatic analysis. In most cases, such a value is a result of considerable disturbances in the signal. In addition, several other quality indicators are analyzed including the coverage of the largest and second largest beat classes, the presence of low signal-to-noise ratio in some beat classes, the presence of beat classes with only one included beat (or disturbance) and the frequency of too close beats.

### *Rhythm sorting*

Finally, rhythm sorting is performed based on the above parameters. Each recording is marked as either of *RR series not accepted* (UNACC), *Low priority* (LOW) containing regular rhythms, or *High priority* (HIGH) containing irregular rhythms. The parameter PSIM is used to determine whether the RR series is acceptable or not and the parameters  $RR_{\text{std}}$ ,  $RR_{\text{pm}60}$ , PAVB, PAME, PACC, PCLU and PSTR are used to divide the remaining signals into the high and low priority groups. In addition, each recording is given additional marks for *Quality issues* (QUAL), *Obvious SVES/bigemini rhythm* (SVES/BIGE), *Fast rhythm* (FAST), and *Wide QRS complex* (WIDE). All parameter thresholds were set based on an annotated standard 12-lead

ECG database containing 912 sinus rhythm cases and 483 atrial fibrillation cases.

### 3. Database

An annotated database containing 2837 one-lead ECG recordings from 103 patients with 30 s duration was used to evaluate the performance of the proposed sorting algorithm. The signals were recorded using Zenicor thumb-ECG devices, see Sec. 1, and are part of a larger research study involving 13000 75–76 year-olds in Sweden. Each recording was visually inspected by a physician and marked as either sinus rhythm ( $n=2545$ ), atrial fibrillation ( $n=56$ ), other arrhythmia ( $n=80$ ), poor quality ( $n=76$ ) or unknown ( $n=37$ ). A small group was not annotated ( $n=43$ ). In average, there were 28 recordings per patient and recordings from 12 of the 103 patients were at least once annotated as AF.

### 4. Results

The proposed algorithm was able to calculate the above described parameters for all of the 2837 recordings in the study. The sorting performance of the proposed algorithm is presented in Tab. 1. The results show that the user of the algorithm can focus on 9.4% ( $n=267$ ) of the entire database and in that high priority group find 55 out of 56 AF cases according to the annotation. In 104 cases (3.7%), the RR series is difficult to interpret due to that it consists of a too large mix of beat morphologies. This means that 86.9% ( $n=2466$ ) of the recording are placed in the low-priority group and do not contain AF-like beat patterns. One signal annotated as AF is placed in the low-priority group due to a too regular RR series. This patient is, however, not missed since there were 32 recordings from this patient of which 26 were annotated as sinus rhythm and 6 as AF. The algorithm places 24 of the recordings in the low priority group due to a regular RR series and 8 in the high priority group due to an irregular beat pattern. All of the 12 patients showing an irregular RR series at least once were found by the algorithm.

In Tab. 1, it can also be seen that 130 recordings annotated as sinus rhythm end up in the high priority group. Four examples of these cases are shown in Fig.1 which all have considerably larger degree of irregularity in the RR series compared to the missed one annotated as AF. These cases are representative for the rather large group of cases annotated as sinus rhythm but with some degree of irregularity in the RR series which motivates the high-priority indication.

Many of the recordings in this group are, however, marked with either of QUAL, FAST or SVES/BIGE indicating that the algorithm has detected additional information about the rhythm, see Tab. 2. For example, out of

Table 1. Summary of the sorting performance. The table shows the number of detections in each group (LOW, HIGH, and UNACC) for each of the different types of signals in the database according to the annotation.

<i>Annotation</i>	<i>All</i>	<i>LOW</i>	<i>HIGH</i>	<i>UNACC</i>
No diag.	43	30	10	3
SR	2545	2357	130	58
AF	<b>56</b>	<b>1</b>	<b>55</b>	<b>0</b>
Other arrh.	80	41	37	2
Poor qual.	76	21	18	37
Unknown	37	16	17	4
TOTAL	2837	2466	267	104
TOTAL %	100%	86.9%	9.4%	3.7%



Figure 1. Four signals annotated as normal sinus rhythm which the algorithm places in the high priority group due to an irregular beat pattern which cannot be explained by quality issues, SVES/bigemini behavior or other ectopic beats. The ten first seconds out of 30 are shown.

the 130 cases in the high priority group which were annotated as sinus rhythm, 46 cases had at least some indication of quality problems in the RR series that may have caused the recording to show an irregular beat pattern, 5 cases had a very fast beat pattern which makes it more difficult to evaluate irregularity and 15 cases had a pronounced SVES or bigemini pattern in the RR series which thus explains the very irregular beat pattern in these cases. The number of annotated sinus rhythm cases in the high priority group which could not be explained by poor quality or obvious SVES/bigemini rhythms was 69.

In addition to the rhythm analysis, it can be seen in Tab. 2 that in total 115 (101+14) cases out of the 2837 showed a wide QRS complex. It should, however, be noted that there in the database are approximately 28 recordings per patient which means that only a few of the 103 patients had a wide QRS complex.

The performance of the P wave waveform analysis

Table 2. Additional sorting information given in the following order (QUAL, FAST, SVES/BIGE, WIDE). For UNACC, only the number of QUAL is given.

Annotation	LOW	HIGH	UNACC
No diag.	10,0,6,2	7,0,0,0	3
SR	246,37,4,92	<b>46,5,15,8</b>	56
AF	0,0,0,0	6,1,1,0	0
Other arrh.	3,1,2,3	5,0,7,1	2
Poor qual.	17,0,0,4	17,3,1,5	37
Unknown	5,0,0,0	4,0,2,0	4
TOTAL	281,38,12, <b>101</b>	85,9,26, <b>14</b>	102

is illustrated by two examples, see Fig. 2. Figs. 2(a) and (c) show the concatenated P wave interval signal and the corresponding modeled signal in the upper and lower panel respectively for a sinus rhythm case. In this case, where there are distinct P waves, the model error PAME contains 12% of the original signal energy based on PACC=96% of the blocks. The main waveform cluster covers PCLU=96% of the blocks and the similarity within the cluster was 0.87 (max 1). For comparison, the AF example in Figs. 2(b) and (d) has PAME=30% with only PACC=23% accepted blocks. The main waveform cluster covers only PCLU=12% of the blocks with and internal similarity of PSTR=0.68.

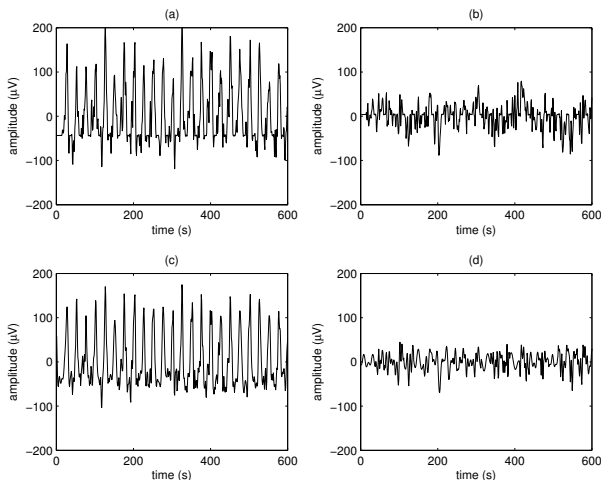


Figure 2. Concatenated P wave interval signal and the corresponding modeled signal in the upper and lower panel, respectively, for a sinus rhythm case (left) and an AF case (right).

## 5. Discussion

As shown in the result section, there will always be cases close to the decision line between the high and low prior-

ity groups. In this work, the method has been tuned using an annotated standard 12-lead ECG database. The parameter settings were set in order to make sure that no important cases are missed. The one AF case in the low priority group could be based on the regularity of the signal not being included in the high priority group.

It is interesting to note that the proposed algorithm identified a group of 69 recordings annotated as sinus rhythm in the high priority group which could not be explained by quality problems or pronounced SVES/bigemini pattern. Four of these were shown in the results section and showed to different degrees of irregularities in the RR series.

While it is extremely time-consuming to manually go through all the recordings in large thumb-ECG databases, the proposed algorithm, at present, sorts the entire database in less than 30 minutes.

## 6. Conclusion

In conclusion, the proposed algorithm is able to differentiate between irregular and regular beat patterns and, in addition, within the group of irregular beat patterns differentiate between those that can be explained by disturbances, ectopic beats, and bigemini rhythms. The proposed algorithm considerably reduces the workload in identifying patients at risk for stroke in large ECG databases. Thus, automatic analysis of one-lead ECG databases can quickly guide the physician to find recordings with high probability to contain atrial fibrillation and can automatically indicate if a recording needs to be re-made due to quality problems.

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