AUTOMATIC DETECTION OF ATRIAL FIBRILLATION AND FLUTTER

A Tachogram-based Algorithm for Mobile Devices

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Abstract: Two versions of a new detector for automatic real-time detection of atrial fibrillation and atrial flutter in non-invasive ECG signals are introduced. The methods are based on beat to beat variability, tachogram analysis and simple signal filtering. The implementation on mobile devices is made possible due to the low demand on computing power of the employed analysis procedures. The proposed algorithms correctly identified 436 of 440 five minute episodes of atrial fibrillation or flutter and also correctly identified up to 302 of 342 episodes of no atrial fibrillation, including normal sinus rhythm as well as other cardiac arrhythmias. These numbers correspond to a sensitivity of 99.1 % and a specificity of 88.3 %.

1 INTRODUCTION

Atrial fibrillation (AF) is a widely spread disease and the most frequently diagnosed cardiac arrhythmia in western countries. Approximately 1–5 % of the population in such countries suffer from atrial fibrillation, with increasing percentages at higher patients' ages, reaching an incedence of almost 12 % in male patients at ages over 85. Due to the rising average age in the industrial nations and to the ascending commonness of other established risk-factors, such as hipertension or overweight, experts expect a doubling of the incidences during the next 50 years.

Whereas atrial fibrillation at itself is not a life-threatening disease, it entails dangerous secondary complications, such as embolisms and apoplectic strokes. Approximately 15 % of all strokes are caused by atrial fibrillation.

The timely diagnosis of AF proves to be complicated due to several reasons. First, atrial fibrillation implicates scant perceivable symptoms and is mostly not noticed by the patients themselves. Second, in early stages the disease occurs in irregular episodes with unpredictable times of appearance and durations. On the other hand, physicians have ever fewer time spendable on each patient, making it impossible to analyze long-term ECG manually.

Therefore, automatic detection of atrial fibrillation in electrocardiograms is and will be increasingly important and necessary during the next decades. (Heeringa et al., 2006; Ringborg et al., 2008; Hohnloser et al., 2005)

2 ATRIAL FIBRILLATION AND FLUTTER

The healthy heart beats at a regular rhythm with approximately 60–80 bpm (normal sinus rhythm, NSR), where the electrical excitation for each beat starts at the sinus node and subsequently spreads over the atrium and ventricles.

In contrast, during atrial fibrillation, the vestibules are stimulated at a frequency of 350–600 activations per minute, causing a quasi constantly circulating excitation. This condition provokes a dysfunction of the blood pumping activity in the atrium, creating the risk of blood accumulation and therefore the risk of embolisms. Also, the constant stimulation of the atrium does not allow the organized and periodic conduction of the activation toward the chambers. Rather, the points in time of the simulation propagation toward the chambers and the so induced heartbeats are random and the time intervals between two heartbeats (RR interval) become absolutely irregular and chaotic.

In the ECG, atrial fibrillation is perceptible by

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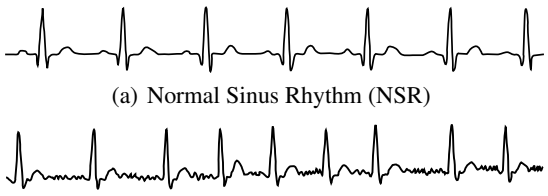
high disparity of the length of the RR intervals – meaning very irregular heartbeat, the absence of the p-wave and through a constant baseline fibrillation, caused by the constant activation of the atrium. Figure 1 shows the ECG of atrial fibrillation compared to the ECG of normal sinus rhythm.



(a) Normal Sinus Rhythm (NSR)

(b) Atrial Fibrillation (AF)

Figure 1: Comparison of the morphology of an ECG signal for normal sinus rhythm and atrial fibrillation.

Atrial flutter (AFLUT) appears as a disease that shows big similarities to atrial fibrillation, and also only differs in minor aspects concerning the morphology of the ECG and specially concerning the heart beat rhythm. Due to this reason, in the following atrial fibrillation (AF) refers both, atrial fibrillation and atrial flutter.

3 STATE OF THE ART

Automatic detection of atrial fibrillation has been base of research during many years and several methods have been developed in this field, predicated on different approaches. A distinction into methods appropriate for the detection on invasive ECG signals and those for detection on non-invasive signals has to be made, due to the discrepancy of the signal quality, the signal-to-noise ratio (SNR) and the information contained in the signal.

The two general main approaches investigated for the detection of AF are the analysis of the signal-baseline between heart-beats, including baseline variation, zero-crossing and detection of p-waves (Kim et al., 1995), and the analysis of the rhythm, including variance of RR intervals (Logan and Healey, 2005), density allocation of RR intervals (Tateno and Glass, 2000), analysis with artificial neural networks (Artis et al., 1991) and analysis in frequency domain (Sadek and Ropella, 1995), between others. In the field of mobile devices, detection on non-invasive signals is required and in this range the approach of rhythm analysis is the most commonly used.

Furthermore mobile devices demand low computing power costs. Therefore complicated and computationally intensive procedures, such as artificial neural networks or transformation into the frequency domain should be avoided.

In addition, the length of the analyzed datasets has to be taken into consideration at the examination of different algorithms, since the longer the contemplated dataset, the easier will the detection of a certain signal pattern be. However, short analysis sections are preferable for prompt detection.

4 DATASETS

In the run-up to this work an adequate, statistically relevant test-database was generated, based on the following four source-databases.

- Physionet MIT-BIH Atrial Fibrillation Database (Goldberger et al., e 13)
- American Heart Association (AHA) Database (Goldberger et al., e 13)
- ECG signals recorded at the Institute for Signal Processing Technology (ITIV), Universität Karlsruhe (TH), Germany
- ECG signals recorded at the University Hospital Tübingen (UKT), Germany

These databases include recordings with normal sinus rhythm, atrial fibrillation and flutter as well as other cardiac arrhythmias, such as unifocal and multifocal premature ventricular contraction (PVC), bigeminy, trigeminy and quadrageminy, couplets, triplets and tachycardia.

The created test database consists of 782 five-minute datasets with representative ECG rhythms, that were classified into ”atrial fibrillation datasets” (AF) and ”no atrial fibrillation datasets” (NOAF).

Finally, out of the 782 records 440 were categorized as AF and 342 as NOAF. Out of the latter 142 show normal sinus rhythm or isolated PVC (NSR) and 200 show other strong arrhythmias (OAR).

Table 1: Overview of the final test database.

ECG-Type	# Datasets	Total Length
AF	440	2200 min
NSR	142	710 min
OAR	200	1000 min
All	782	3910 min

The length of five minutes was chosen as a compromise between easier detection on longer entities and prompt detection on shorter episodes. The final decision over the contemplation period for detection was taken in collaboration with physicians of the University Hospital T”ubingen.

In order to obtain a standardized database, as well as to ensure the possibility of saving other additional records, such as tachograms, results, etc. along with the original ECG signals, all 782 ECG records were converted into the Unisens format (Kirst et al., 2008; Kirst and Ottenbacher, 2008).

5 ALGORITHM

According to the requirements of a mobile device, an algorithm was developed that reliably detects atrial fibrillation on non-invasive ECG signals under adherence of low processing power costs. The proposed method rests upon the analysis of the rhythm of the heart beats and is more precisely based on the analysis of the RR interval tachogram.

Furthermore the developed algorithm divides into two separated detection methods, the PPV-Detector and the PPV-MF-Detector. Whereas the further constitutes the basic detection algorithm, the PPV-MF-Detector answers an extension, achieving an improvement of the detection quality.

5.1 ECG Premachining

The tachogram-based analysis requires a premachining of the ECG signal, consisting of the QRS detection and the computing of the actual tachogram.

5.1.1 QRS Detection

QRS detection creates a list containing the points in time of the heartbeats. Numerous QRS-detection-algorithms have been published. In this work the Open Source ECG Analysis algorithm has been used for the QRS detection (Hamilton, 2002).

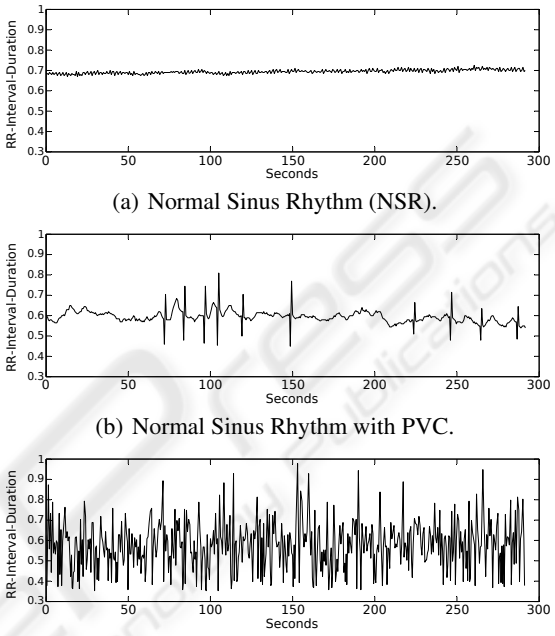
5.1.2 Tachogram Generation

The tachogram is a heart rate variability signal (HRV), that considers not only normal heart beats but also PVC and that measures the beat-to-beat variations in the heart rate. It shows the RR interval duration between the actual and the previous beat over the time of the actual beat.

$$RR_i = t(R_i) - t(R_{i-1}) \tag{1}$$

This means, for each heartbeat the time interval to the previous heartbeat is calculated. The result corresponds to the value of the tachogram at the point in time of the contemplated heartbeat.

The tachogram then provides information about the ECG rhythm and its regularity. A regular heartbeat, such as appears in NSR, will generate a flat tachogram with an almost constant value. Arrhythmias in the ECG will lead to amplitude varieties and a heart beat as irregular as it occurs during AF will lead to a tachogram with an appearance similar to white noise. Figure 2 shows the tachograms of a NSR-ECG, a NSR-ECG with PVC and an AF-ECG.



(a) Normal Sinus Rhythm (NSR).

(b) Normal Sinus Rhythm with PVC.

(c) Atrial Fibrillation (AF).

Figure 2: Comparison of the tachograms of different ECG signals.

5.2 PPV-Detector

The PPV-Detector comprehends the basic detection method of the proposed algorithm and represents a fully functional AF detection algorithm by itself. PPV-Detector stands for ”Peak-to-Peak and Variance Analysis Detektor”.

Methodically, the PPV-Detector divides the 300 seconds long datasets into 30 equally long 10 second segments. Each segment is further on analyzed separately and individually.

5.2.1 Peak-to-Peak and Variance Reckoning

The peak-to-peak value PP defines the maximum difference between any two RR intervals in one segment, and equals the difference between the maximum and the minimum amplitude inside the examined segment. It is therefore calculated as

$$PP(s_n) = \max(RR(s_n)) - \min(RR(s_n)) \quad n = 1,..,30, \tag{2}$$

where s_n corresponds to the segment n and $RR(s_n)$ to the set of RR interval durations of segment s_n.

The variance of the set of RR interval durations of each segment s_n is calculated by

$$\mathrm{var}(s_n) = \frac{\sum_{i=1}^{I}(RR_i - \mathrm{mean}(s_n))^2}{I-1}, \quad (3)$$

$$\mathrm{mean}(s_n) = \frac{\sum_{i=1}^{I} RR_i}{i}, \quad (4)$$

where I corresponds to the amount of RR interval values RR_i in each segment s_n.

5.2.2 PPV-Detector Decision Tree

The datasets are classified as AF and NOAF by using a decision tree based on threshold comparisons. This decision tree can be devided into two separate parts, where the first analyzes the individual segments, whereas the second classifies the entire dataset into either AF or NOAF.

In a first step the classification for every single segment is made. Thereby, for each segment s_n the $PP(s_n)$ is calculated. Each segment with a PP higher than 0.2 is classified as *AF-typical* whereas those with a PP smaller than this are classified as *not-AF-typical*. A decision for not-AF-typical leads to the increment of a counter in order to keep track of the number of not-AF-typical segments in the dataset. In addition, only in this case the variance Var of the concerned segment is calculated and saved in a buffer.

Figure 3 shows this first part of the flow chart for the PPV-Detector decisions.

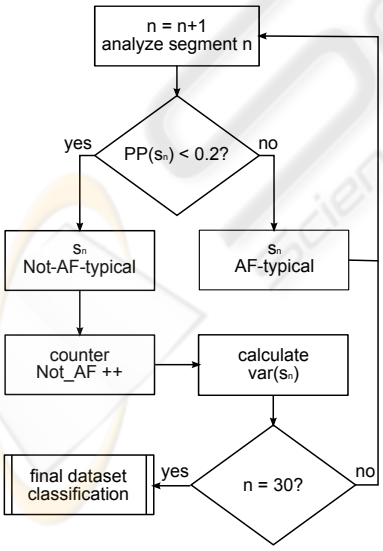


Figure 3: Flowchart for the segment classification.

Once every segment in the dataset has been treated according to the explained method, a final diagnosis of the dataset is reached by the second part of the detection algorithm as follows.

If the number of not-AF-typical segments exceeds 10, the dataset is immediately classified as NOAF. If this is not the case, the buffered variances $\mathrm{Var}(s_n)$ are taken in consideration and are compared to another threshold. If more than four of the buffered variances out of the dataset segments are smaller than 0.00075, the dataset will again be classified as NOAF.

Only if the number of not-AF-typical segments is smaller or equal to ten and less than four of the buffered variance are smaller than the set threshold, the dataset will be diagnosed as AF.

Figure 4 shows the second part of the flow chart for the PPV-Detector, in which the final diagnosis decision for the dataset is made.

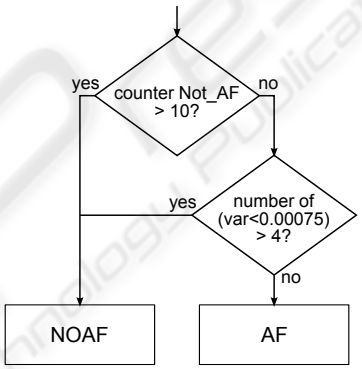


Figure 4: Flowchart for the final dataset classification.

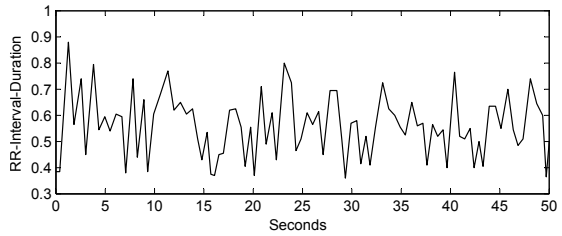
5.3 PPV-MF-Detector

Whereas the PPV-Detector algorithm consists of a very simple AF analysis focused on the reckoning of peak-to-peak values and variances, the PPV-MF-Detector understands a further analysis, that is based on the PPV-Detector, but includes a second analysis helped by morphological filters (MF).

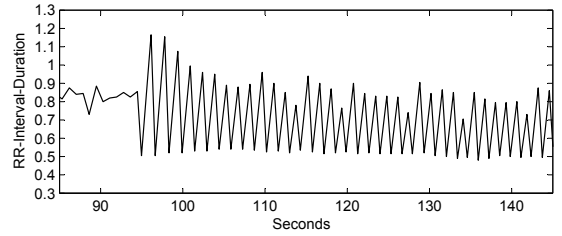
The fundamentals of this method lie in the fact, that strong structural differences, that do not show in the analysis of peak-to-peak values and variances, can be found between tachograms of atrial-fibrillation ECG signals and those obtained from other strong arrhythmias, such as bigeminal premature ventricular contractions (bigeminy), trigeminal premature ventricular contractions (trigeminy), quadrageminal premature ventricular contractions (quadrageminy) or series of couplets and series of triplets. These structural differences consist of the existence of repeating morphologies or structures in tachograms of such other arrhythmias.

Figure 5 clearly shows these differences in the tachograms of atrial fibrillation compared to

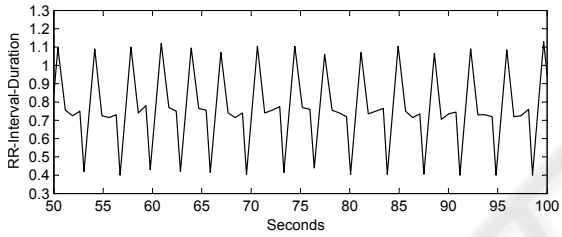
bigeminy and quadrageminy.



(a) Atrial Fibrillation (AF)



(b) Bigeminal PVC



(c) Quadrageminal PVC

Figure 5: Comparison of the tachograms of different arhythmias.

The idea of the PPV-MF-Detector is to use morphological filters in order to suppress these repeating structures in the tachogram. The result of this procedure is a second, modified tachogram, that is then again analyzed by a basic PPV-Detector.

5.3.1 Morphological Filtering Process

Morphological filters find their origin in the area of image processing, where they still today find the most frequent use. Nevertheless these filters have also found applications in signal processing, mainly in the field of noise reduction but also to suppress specific signal structures.

The basic idea of morphological filtering consists of the sum or rest of a structuring element with the signal that is to be filtered, being the two most important operations *Opening* and *Closing*. Morphological filtering has been previously applied in the field of biosignal processing as in (Chu and Delp, 1989).

Since the form and length of the structuring element of a morphological filter influence the result of the filtering process in an essential way, an adequate structuring element has to be found for each tachogram. It has been proved during this work, that in general a structuring element with a length of four datapoints and with the morphology of a rectangle-function is the most adequate choice for this filtering. The exact values of the 4 points of the structuring element are however adapted to each dataset that is to be analyzed.

In our method, the amplitude of the first and the fourth point of the structuring element correspond to the mean value of the 75 lowest points of the original tachogram, while the amplitude of the second and the third point of the structuring element correspond the mean value of the 75 highest points of the original tachogram.

$$SE(1) = SE(4) = \frac{\sum_{i=1}^{75} \min_i(RR(s_n))}{75}, \quad (5)$$

$$SE(2) = SE(3) = \frac{\sum_{i=1}^{75} \max_i(RR(s_n))}{75}, \quad (6)$$

Figure 6 shows the general appearance of form of the structuring element chosen for the morphological filtering of the tachograms.

Figure 6: Form chosen for the structuring element of the morphological filter.

5.3.2 Creation of the Alternative Tachogram

The alternative tachogram is created through a two step procedure.

Previous to the morphological filtering, the mean value of the original tachogram signal is calculated.

Then, the original tachogram is morphologically filtered by sequential implementing a closing and an opening MF operator. For each of these two morphological operations the same, previously calculated, structuring element is used.

Figure 7 shows two tachograms, one of quadrageminy and one of atrial fibrillation in the uppermost graphs. The output signal of this step is shown in the second graphs of the same figure.

In a following step, the resulting signal is rested from the original tachogram, resulting in the Δ-signal. (Graph 3 in figure 7 for quadrageminy and AF respectively).

Finally, for each signal point at which the Δ-signal reaches an amplitude higher then 0.3, the value of the original tachogram is substituted by the mean value of the tachogram. The result signal of this step constitutes the new, alternative tachogram. This result signal can be seen in the lowest graph of figure 7. It

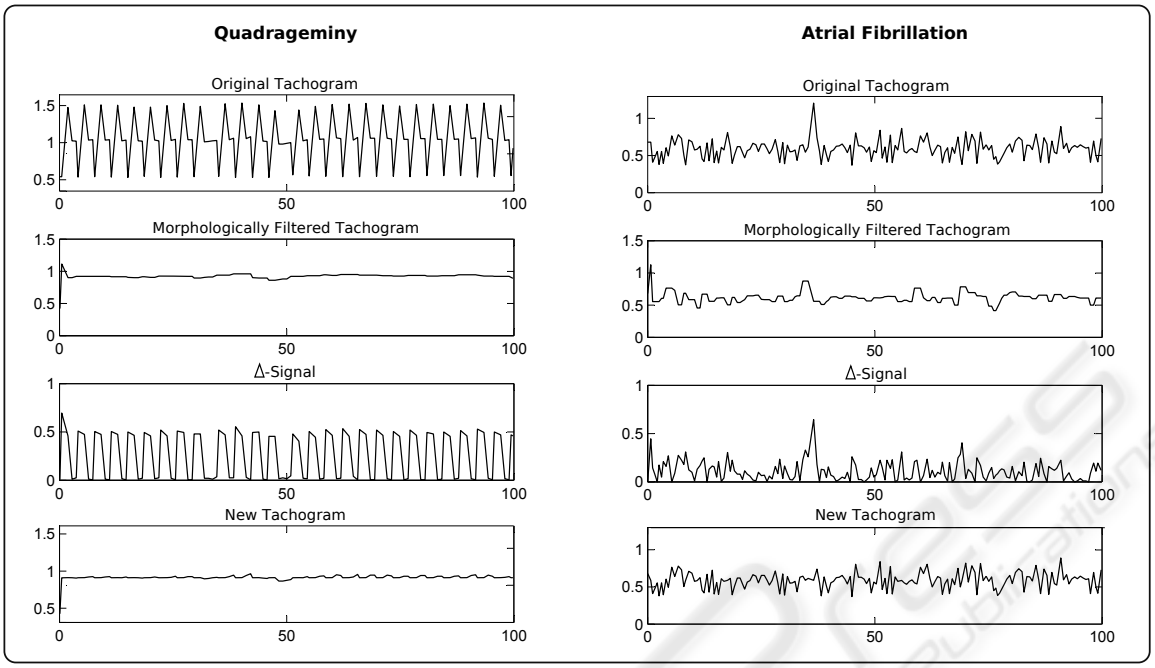


Figure 7: Output signals of the different steps of the creation of the new tachogram. Quadrageminy on the right side and AF on the left side.

is clearly observable that the new tachogram for the quadrigeminy signal shows important disparities with the original tachogram, appearing now as a very constant signal. On the other hand, the new tachogram of the AF signal shows relatively very little differences compared to the original tachogram.

Figure 8 shows the flowchart for the creation of the alternative tachogram signal.

5.3.3 PPV-MF-Detector Decision Tree

The final MF detection algorithm combines the original PPV-Detector with the morphological filtering and creation of the new, adapted tachogram.

The detector diagnoses the ECG signal in two steps. In the first step, the original PPV-Detector diagnoses the ECG signal. Only if the first diagnosis is AF, the PPV-MF-Detector continues with the creation of the alternative tachogram, which is then, once again, analyzed again by a second, slightly adapted PPV-Detector.

For the first, initial PPV-Detecor, the standard PPV-thresholds are to be used. For the second PPV-Detector, the thresholds have been slightly adapted. The threshold values for both PPV-Detectors are listed in table 2. All threshold values have been determined empirically.

Figure 9 shows the decision tree equivalent to the PPV-MF-Detector.

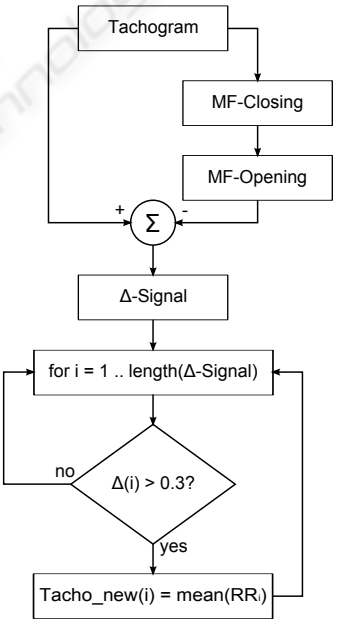


Figure 8: Flowchart for the building of the new, adapted tachogram.

6 RESULTS

An overview of the detection results obtained with the basic PPV-Detector and for the PPV-MF-Detector is displayed in table 3. Here, sensitivity (Se) indicates

Table 2: Thresholds for the PPV decisions.

	PP(s_n)	**# PP**	**Var(s_n)**	**# Var**
basic PPV	0.2	10	0.00075	4
PPV-MF	0.2	10	0.0006	4

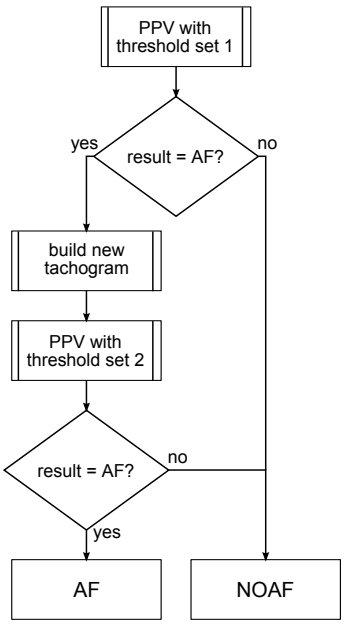


Figure 9: Decision Tree for the final dataset diagnosis for PPV-MF-Detector.

the portion of AF signals that have been correctly detected as AF, whereas the specificity (Sp) denotes the percentage of NOAF signals, this is to say NSR signals and other arrhythmias, that have been correctly detected as NOAF.

Table 3: Detection qualities for the proposed methods.

Detection Algorithm	**Sensitivity**	**Specificity**
PPV-Detector	99.1 %	80.1 %
PPV-MF-Detector	99.1 %	88.3 %

As table 3 shows, both, the PPV-Detector and the PPV-MF-Detector reach the same, very high level of sensitivity. The difference in the qualities of both algorithms rests in the specificity. Here, the PPV-MF-Detector achieves a notably higher percentage than the PPV-Detector, at the expense of an increased necessary computing power in relation to the first.

A more precise look at the results for the different datasets is presented in table 4. It reveals that not only the sensitivity of the two detector versions is equal, but also the specificity for normal sinus rhythm signals is equal and very high for both algorithms. The results differ only in reference to the specificity for ECG signals with arrhythmias other than atrial fibrillation. The quality increase of the specificity between the two algorithms in this domain is of 14 %.

Table 4: Detection Qualities for the different ECG signal conditions.

PPV-Detector						
ECG	**TP**	**FN**	**TN**	**FP**	**Se**	**Sp**
All	436	4	274	68	99.1 %	80.1 %
AF	436	4	—	—	99.1 %	—
NSR	—	—	137	5	—	96.5 %
OAR	—	—	137	63	—	68.5 %
PPV-MF-Detector						
ECG	**TP**	**FN**	**TN**	**FP**	**Se**	**Sp**
All	436	4	302	40	99.1 %	88.3 %
AF	436	4	—	—	99.1 %	—
NSR	—	—	137	5	—	96.5 %
OAR	—	—	165	35	—	82.5 %

7 CONCLUSIONS AND DISCUSSION

Within this article, two alternatives of an algorithm for the detection of atrial fibrillation in ECG signals have been proposed.

As it can be observed by means of the results exposed in section 6, the two algorithm reach very satisfying detection qualities in terms of sensitivity for atrial fibrillation and specificity of normal sinus rhythm. On the other hand, the methods differ noticeably in the specificity regarding ECG signals with strong arrhythmias other than atrial fibrillation. At the expense of a higher demand on computing power, the PPV-MF-Detector produces better results than the PPV-Detector itself.

Both alternatives have been developed focusing on the intention of detecting episodes of AF in a long term electrocardiogram, that are to be flagged for the later revision by a physician and the ultimate diagnosis. On the other hand the algorithms have been developed under the constraints of mobile devices. This is, in the first place, low processing power. Due to the characteristics named earlier, each of the two proposed algorithms has different advantages and disadvantages, so that the ideal choice depends on the precise utilization environment.

In summary the two versions of the detector that have been proposed, provide very high sensitivity being the algorithms based on very simple basic principles, such as threshold comparisons and therefore on very low computing power demands.

8 OUTLOOK

A further improvement of the specificity in the area of other strong arrhythmias, such as bigeminy, trigeminy, couplets, etc., may be reached under a slight increase of computing power demands.

One alternative approach to the detection consists in the suppression of PVC beats previous to the analysis with the PPV- and the PPV-MF-Detectors. A new determination of the thresholds would be necessary in this case.

Another alternative modification of the proposed methods would be the analysis of ECG episodes containing a fixed amount of beats instead of a fixed time period. This would specially simplify the implementation of the methods on mobile devices due to non-variable memory allocations.

Further on, the possibility of distinguishing and diagnosing not only between "atrial fibrillation" and "not atrial fibrillation", but also between the different other arrhythmias should be taken in consideration. Another approach in this area could be the intent of delivering the exact number of PVC beats occurred in one certain ECG segment.

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REFERENCES

Artis, S., Mark, R., and Moody, G. (1991). Detection of Atrial Fibrillation using Artificial Neural Networks. *IEEE Proceedings on Computers in Cardiology*, pages 173–176.

Chu, C.-H. H. and Delp, E. J. (1989). Impulsive noise suppression and background normalization of electrocardiogram signals using morphological operators. In *IEEE Transactions on Biomedical Engineering, Vol 36, NO. 2*, pages 262–273.

Goldberger, A. L., Amaral, L. A. N., Glass, L., Hausdorff, J. M., Ivanov, P. C., Mark, R. G., Mietus, J. E., Moody, G. B., Peng, C.-K., and Stanley, H. E. (2000 (June 13)). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation*, 101 (23):e215–e220. Circulation Electronic Pages: http://circ.ahajournals.org/cgi/content/full/101/23/e215.

Hamilton, P. (2002). Open Source ECG Analysis. *IEEE Computers in Cardiology*, pages 101–104.

Heeringa, J., van der Kuip, D., Hofman, A., Kors, J., van Herpen, G., Stricker, B., Stijnen, T., Lip, G., and Witteman, J. (2006). Prevalence, incidence and lifetime risk of atrial fibrillation: the Rotterdam study. *Europace*.

Hohnloser, P. D. S., Grönefeld, P.-D. D. G., and Israel, P.-D. D. C. (2005). *Prophylaxe und Therapie von Vorhofflimmern*. UNI-MED Verlag, Bremen, London, Boston, 1. edition edition.

Kim, J., Bocek, J., White, H., Crone, B., Alferness, C., and Adams, J. (1995). An atrial fibrillation detection algorithm for an implantable atrial defibrillator. pages 169–172.

Kirst, M. and Ottenbacher, J. (2008). Unisens. http://www.unisens.org.

Kirst, M., Ottenbacher, J., and Nedkov, R. (2008). UNISENS – Ein universelles Datenformat für Multisensordaten. In *Biosignalverarbeitung : Innovationen bei der Erfassung und Analyse bioelektrischer und biomagnetischer Signale*, pages 106–108.

Logan, B. and Healey, J. (2005). Robust Detection of Arial Fibrillation for a a Long Term Telemonitoring System. *IEEE Computers for Cardiology*, pages 391–394.

Ringborg, A., Nieuwlaat, R., Lindgren, P., Jnsson, B., Fidan, D., Maggioni, A., Lopez-Sendon, J., Stepinska, J., Cokkinos, D., and Crijns, H. (2008). Costs of atrial fibrillation in five European countries: results from the Euro Heart Survey on atrial fibrillation. *Europace*, 10:403–411.

Sadek, L. E. and Ropella, K. M. (1995). Detection of Atrial Fibrillation from the Ssurface Electrocardiogram using Magnitude-Squared Coherence. *IEEE Engineering in Medicine and Biology Society*, 1:179–180.

Tateno, K. and Glass, L. (2000). A Method for Detection of Atrial Fibrillation using RR Intervals. *IEEE Computers for Cardiology*, pages 391–394.