Quantification of postoperative atrial fibrillation by automatic analysis of electrocardiograms

A study to find incidence and burden of early postoperative atrial fibrillation after open chest surgical aortic valve replacement through an automatic detection method.

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Abstract

Introduction New-onset postoperative atrial fibrillation (PoAF) is a common complication after open heart aortic valve replacement with an incidence of 22-49%. The result thereof is a decrease in the patient's well-being and an increase in health care costs. The past decades research about the PoAF episode incidence and burden has stagnated. Due to insufficient detection systems these variables are not often registered, impeding research about correlating prognoses or causative factors. In this study a method has been developed for automatic PoAF detection, which has been used to examine the episode incidence and burden and the relation between these variables for patients suffering from new-onset PoAF in the five days after open chest surgical aortic valve replacement.

Method and Results After initial data processing a combination of a Pan and Tompkins algorithm for R-peak detection and an AF detection function made by Applied Biomedical Systems BV was used to enable automatic AF detection for episodes of minimally 30 seconds. Validation of this method demonstrated a sensitivity of 100% and specificity of 92.5%. For the population (n=18) with a total registration time of 1590 hours the weighted mean incidence per 24 hours was 12.73 (±12.98) and the weighted mean burden ratio 0.105 (±0.168) within the six days after surgery. The second postoperative day shows the highest episode incidence, though insignificant. The burden remains fairly constant from the second until the fifth postoperative day. No correlation is observed between incidence and burden.

Discussion As longer episodes have a different effect on severity of PoAF and prognosis, the burden might be a new indicator for this. Limitations of this research consisted mainly of incomplete and inconsistent data. For this reason, recommendations are being made about systematic recording of ECGs and artifact handling. Further research could focus on investigating a larger population, variation in episode length and correlation between PoAF episodes and hemodynamic factors.

Keywords PoAF; postoperative atrial fibrillation; incidence; burden; arrhythmia; AVR; aortic valve replacement; ECG; electrocardiogram; AF detection; Pan and Tompkins.

Preface

This study has been performed on the occasion of the multidisciplinary assignment for obtaining a bachelor's degree in Technical Medicine at the University of Twente. It provided us the opportunity to implement and present the knowledge gained during our three year bachelor program. We worked with great joy on the project discovering software as Matlab, Powershell, Excel, SPSS and Latex more in depth. We learned how to gain and combine information from different stakeholders and sources to make something of our own. The technological setbacks taught us how not to underestimate the size of data and overestimate the power of computers.

We would like to thank Natasja de Groot, Paul Knops and Lex van Loon for the supervision during this project. Richard Houben, Ameeta Yaksh, and Klaas Poortema are thanked for their specialistic insights and Marly van Assen for guiding the process by asking 'why?' so many times. Special thanks to Christophe Teuwen who was always available to respond to our questions and demands and show us the way through the Erasmus Medical Centre.

Machteld Boonstra, Kicky van Leeuwen, Freeke Porte and Feline Spijkerboer

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Introduction

1.1 Postoperative atrial fibrillation

A common treatment for aortic valve insufficiency is aortic valve replacement (AVR). This surgery can cause several complications as stroke, a myocardial infarction or a cerebral infarction. [1] Especially new-onset postoperative atrial fibrillation (PoAF) occurs in 22-49% of the patient population. [2–5]

The impaired systolic function of the atria, caused by atrial fibrillation (AF), leads to stasis and gives rise to serious complications like thromboembolic diseases, stroke and heart failure. This results in increased morbidity and mortality and prolonged hospital stays. [2, 3, 6, 7] Even though the consequences can be severe and extra costs associated can pass €8000 per patient, little is known about the pathophysiology of PoAF. [8, 9]

Normally the heart contracts in the sinus rhythm which implies a regular heartbeat that only varies slightly with respirations. In case of arrhythmias this sinus rhythm is disturbed. AF is characterized by an irregular rhythm caused by spontaneous depolarizations throughout the atria. [10] The atrial frequency rises up to 400-600 beats per minute resulting in a vibration of the atria which prevents them from contracting. [11] These high frequent pulses are subsequently submitted to the AV-node which passes on the signal in an irregular ventricular frequency between 75-175 beats per minute. An example of an ECG of the sinus rhythm and AF rhythm can be seen in figure 1.1.

AF is being described in terms of incidence and burden. The incidence is the number of AF episodes of at least 30 seconds that occur. [12] The highest incidence of PoAF episodes is observed on the second and third postoperative day after AVR. [2, 8, 13, 14] The AF load experienced by patients is defined as burden. This is defined as the ratio of total time a patient suffers from PoAF per unit of time. A higher burden implies an increase in mortality, disability adjusted life style and healthcare costs. [15, 16]

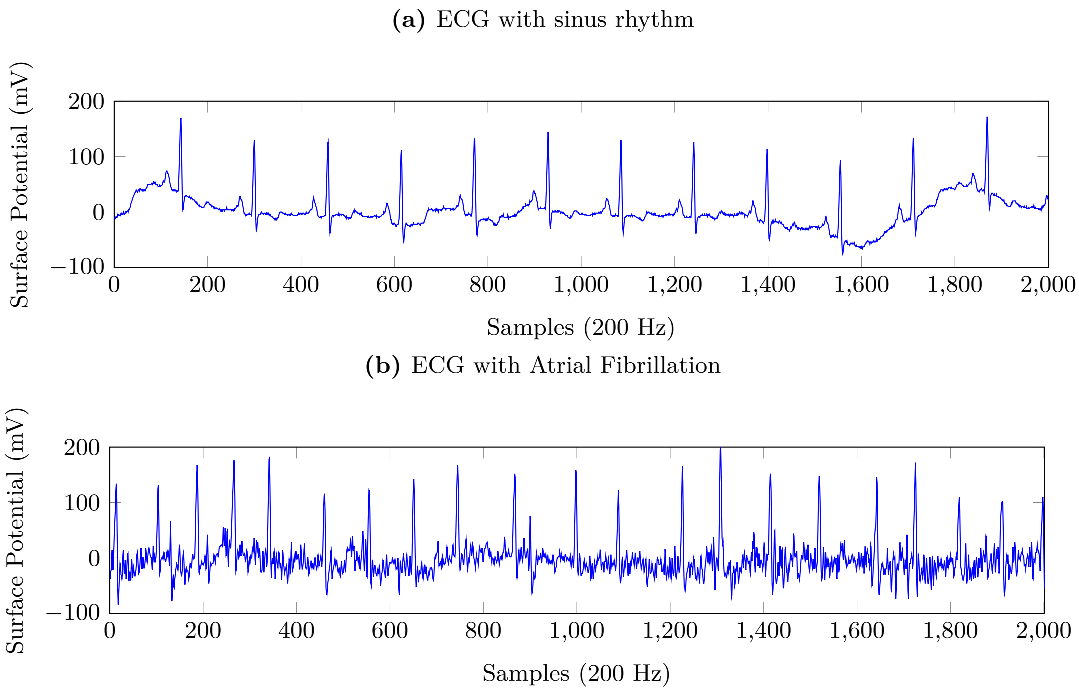


Figure 1.1: Example ECG signal with atrial fibrillation (a) and ECG signal with sinus rhythm (b) in the same patient.

1.2 PoAF detection from ECG

To broaden the knowledge about the origin of PoAF, ECGs recorded at the Erasmus Medical Centre (EMC) were analyzed to quantify burden and incidence. The time after surgery the patient's ECG is being monitored, first on the intensive care unit (ICU) and afterwards on medium care unit (MCU). Currently, details about PoAF are generally not reported, because the PoAF is often intermittent and therefore either not noticed by the medical staff or depreciated.

The data about the incidence and burden is rarely saved or analyzed for research, because detection is complicated. Currently the ECGs are being analyzed semi automatically by medical specialists and the algorithms of Synescope^{TM} (Sorin Group$^{©}$), a multichannel Holter scanning software. Analysis is done by labeling the rhythm as normal (N), atrial fibrillation (AF), and annotating other arrhythmia. This method is seen as the gold standard, but lacks efficiency and is time-consuming.

Automatic AF detection software is being applied in some clinical settings, mainly in implantable devices. However, this software is not widely used for detection of AF in standard 12 lead ECG. This is due to the fact that most detection software lacks specificity and therefore generates insufficient accurate results. Additionally existing software struggles with processing real data because it often contains periods of artifacts or missing data. Examples of these ECG characteristics can be seen in figure 1.2.

In this study an algorithm for automatic AF detection developed by Applied Biomedical Systems B.V. [17] is used to generate a more efficient way of analyzing these sets of data. This software is based on the irregularity of RR-intervals to detect AF. The variability and frequency of RR-intervals is determined and compared to a basis rhythm defining whether AF is present or not. It has a sensitivity of 93-100% and a specificity of around 94-95%. [18–20]

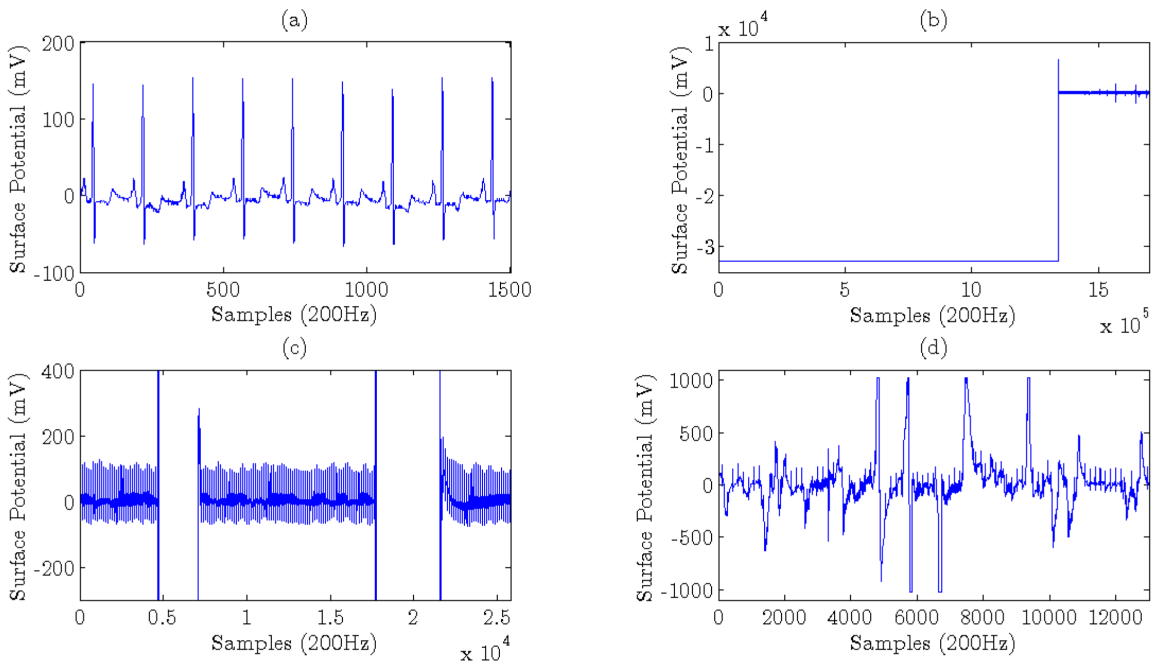


Figure 1.2: Examples of artifacts that can be found in the ECGs. (a) Shows a good quality ECG. (b) Shows an inital flatline where no registration was made. (c) Shows how the signal can drop to extreme values. (d) Shows extreme distortion.

1.3 PoAF Incidence and burden

AF can cause electric, contractile and structural remodeling in the atrial tissue. [21] During electric remodeling the refractory period is significantly reduced. [6] The length of the P-wave is shortened which allows more re-entering of wavelets in a shorter time which might increase sensitivity for AF. [21, 22] If the duration of the AF episodes increases, recovery of the atria seems to takes more time and a change in contractile function occurs. [21] These changes indicate a correlation between the AF burden and the recovery of the atria, thus a higher vulnerability to AF and a higher episode incidence. By this means the burden of AF could be a predisposing factor for the persistence of PoAF as well as the risk for thromboembolic diseases. Boriani et al. [23] puts forward the importance of analyzing the AF burden in order to get to know more about this risk.

Many studies show a peak incidence of patients suffering from PoAF on the second and third postoperative day. [2, 8, 13, 14] However the episode incidence and burden patients suffer from postoperatively have little been studied, as far as the research department of the EMC is concerned. [24] Though the average burden and incidence are expected to follow the same pattern in time, this does not necessarily mean that a higher burden implies a higher incidence or the contrary is true. For example a low incidence can be associated with a high burden as the episodes are long lasting. As for the relation between the incidence and burden no significant correlation has been found.

Due to the inconclusiveness about the origin of PoAF, the current treatment of PoAF is mainly symptomatic instead of focused on prevention. When getting a better understanding of the causes and risk factors associated with AF, focus of treatment can be shifted from symptomatic to preventive.

Our method and results give a starting point for further research to discover correlations between PoAF burden and predictive and prognostic factors. This will contribute to a broadening of the knowledge about the underlying principle of the manifestation of AF. With a new automatic method for the detection of PoAF it is easier to quantify incidence and burden, include this in the patient status and use this information for research on PoAF.

2

Method

2.1 Population

The study population (n=18, 12 male) exists of patients treated at the Erasmus Medical Centre in Rotterdam who underwent an aortic valve replacement by open chest surgery. This study was approved by the institutional medical ethical committee (MEC 2012-481). These patients have had constant rhythm registration and suffered from postoperative atrial fibrillation during ICU and MCU hospitalization. Excluded from this population were patients of whom more than one empty or corrupted .ecg file per dataset was present or many overlapping files of rhythm registration were available.

2.2 Data processing

A dataset of the population was made available by the department of Translational Electrophysiology of the Erasmus Medical Centre. To obtain this data, the EMC first registered the ECGs of the patients with bedside monitors of Draeger Infinity™ and then saved these at a sampling rate of 200 Hz as compromised compoz-files (.cpz) using the eData Taperec system. This data was then converted to the standard Holter format supported by the International Society for Holter and Noninvasive Electrocardiology (ISHNE), which creates an .ecg file. Subsequently the files were decompressed by TapeRec creating different ISHNE (.ecg) files for each patient, labeled with the name of the patient and hospital ward. The recordings were then split into pieces of no longer than 24 hours, so the files were compatible with Synescope™ and was organized by creating a subfolder for each patient containing the ISHNE files. These files were named following the structure of Pt001_Name_ICTH_date_1.ecg. In this format, the dataset was made available for the research.

Processing and analyzing this data has been done in Matlab. Since Matlab has no built in tool for reading ISHNE files a function provided by the Telemetric and Holter ECG Warehouse is used to import the ECGs in Matlab 2015a. [25] The V2 lead has been selected as the channel to apply analysis on, because it is most prominent. All operations executed on the dataset have been visualised in figure 2.3 on page 14. All scripts used for further analysis are described in the Appendix 6.2.

2.3 Detection of atrial fibrillation

2.3.1 RR intervals

To detect atrial fibrillation in the ISHNE files, the Matlab executable of MyDiagnostick firmware v1.3.1, made and provided by Applied Biomedical Systems BV, has been used. The input of this function are RR-intervals defined in samples of five milliseconds. To create the RR-interval array in Matlab, the following methods have been analyzed and tested on accurateness, running time, and artifact handling:

1. *Matlab functions based on the detection algorithm designed by J. Pan and W.J. Tompkins*
   This algorithm is a real-time QRS detection which first preprocesses the ECG signal whereafter QRS complexes can be detected. J. Pan and W.J. Tompkins stated this algorithm detects 99.3% of the QRS complexes correctly, when correctly implemented. [26] This algorithm is widely used and implemented in Matlab, such as:

   (a) *A complete implementation in Matlab developed by H. Sedghamiz from the Linkoping University*
   This implementation is very accurate but takes about half an hour per ISHNE file to run on the available computers, implying that it will take about four hours per patient. Furthermore, during the detection many errors occurred delaying the process.

   (b) *A simplified version of the Matlab function of H. Sedghamiz*
   This script is similar to the one described previously, it runs a little faster but is less accurate.

   (c) *A complete implementation in Matlab developed by Applied Biomedical Systems BV.*
   R. Houben developed a script also based on the Pan and Tompkins algorithm. It has a high sensitivity and specificity and takes less time than the Pan and Tompkins functions stated above. After an alteration in the script it was also able to deal with the artifacts better.

2. *A Matlab script based on the function 'find peaks'*
   This script, designed by ourselves, is based on finding peaks with a minimum height and a minimum time difference between peaks. In comparison to the Pan and Tompkins method, the accuracy is low, the running time about 5 to 10 minutes shorter per file and excluded artifacts well.

3. *Text files generated by Synescope^{TM}*
   The program Synescope$^{\text{TM}}$ used by the Erasmus Medical Centre detects the RR-intervals and a score is being given for every beat stating the type of rhythm. This data is manually checked and altered by the medical specialists. Since this data was already generated, it was quick to extract and import in Matlab. Artifacts were excluded due to the manual check.

In this research a RR-peak detection program based on the Pan-Tompkins algorithm is used to extract the RR-interval arrays (option 1). This algorithm detects real-time QRS complexes by analyzing slope, amplitude and width. When correctly implemented in Matlab, it detects 99,3% of QRS complexes and makes use of a patient specific threshold and RR interval limit. This provides an adaptive approach and thereby an accurate use on ECG signals with various morphologies. [26]

From the three suboptions of option 1, option 1c is implemented and used in this analysis. This script was the fastest of the Pan-Tompkins scripts to run, and after a small alteration worked well in detecting the RR-peaks for the files of 24 hours.

The other options were not implemented due to their disadvantages. Option 2 was eliminated, because it had little advantage over the other solutions, and was most prone to inaccurate RR-peak detection. Option 3 appeared not be a possibility since the RR-intervals detected by Synescope™ were manually altered and therefore did not make the AF detection fully automatic.

2.3.2 AF score

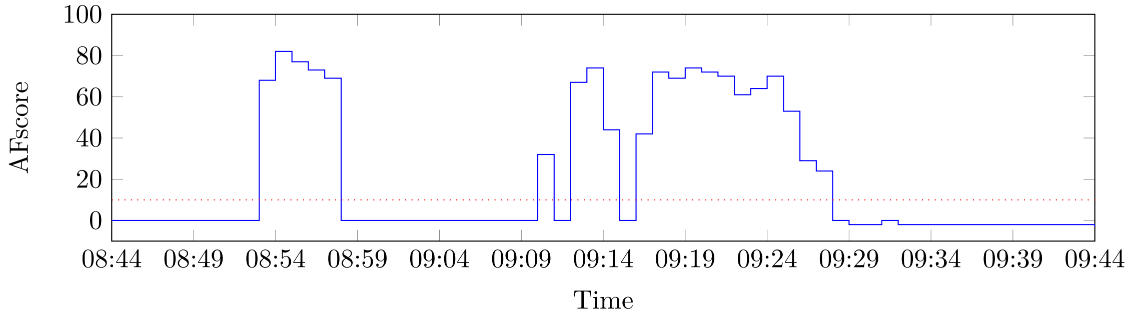
To generate an AF score, an array of RR-intervals per 60 seconds is given as input for the AF detection function of MyDiagnostick firmware v1.3.1 made by Applied Biomedical Systems BV [17]. The AF score is a value between 0 and 100 representing the likelihood for the presence of AF for that minute. This tool has a sensitivity of 93-100% and a specificity of around 94-95% with a cutoff value of 10. [18, 20] We therefore assume that the results received by using this tool are valid.

After generating the AF score we turn an AF score between 0 and 9 into a 0 (no AF) and between 10 and 100 into a 1 (AF). This is visualised in figure 2.1. It is possible that some timeframes do no contain (sufficient) data, these generate an AF score of -1, -2 or -3 depending on the type of error. The definition of the AF scores can be seen in table 2.1.

Table 2.1: Meaning of the AF scores.
Explains the meaning of the AF scores given after implementing the cutoff value of 10. The negative numbers are errors and indicate that the AF score could not be calculated.

AF score	Definition
0	Likelihood of AF 0-9
1	Likelihood of AF 10-100
-1	Error: Indices out of bounds
-2	Error: Less than 20 RR-intervals are given as input
-3	Error: No value as input

(a) An example of AF score



(b) An example of AF score, binary

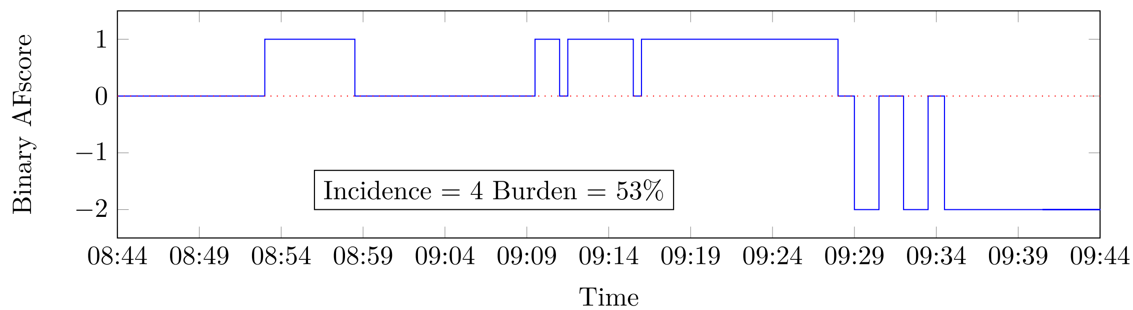


Figure 2.1: AF score before and after applying the cutoff value of 10, displayed by the red line in (a), for which the AF score in (b) turns into either a 1 or 0. Negative numbers are errors and are preserved. This example shows an incidence of 4 and burden of 0.53.

An AF episode has been defined as a period of 30 seconds in which AF occurs. [12] Therefore, it is favorable to produce an AF score per 30 seconds instead of 60 seconds. In antiphase, two arrays of AF scores have been generated per file. This means the first array generates an AF score for 0-60 seconds, 60-120 seconds, etc. and the second array for 30-90 seconds, 90-150, etc. Each AF score in the array is being doubled to compile to a time array per 30 seconds. Then the two arrays are combined, to one new array representing the implied AF score per 30 seconds, an example of this can be seen in table 2.2).

Table 2.2: Example AF score.
Array 1 and 2 represent a binary AFscore per minute, doubled to match the time array (per 30 seconds). Subsequently combined to generate the final AF score per 30 seconds.

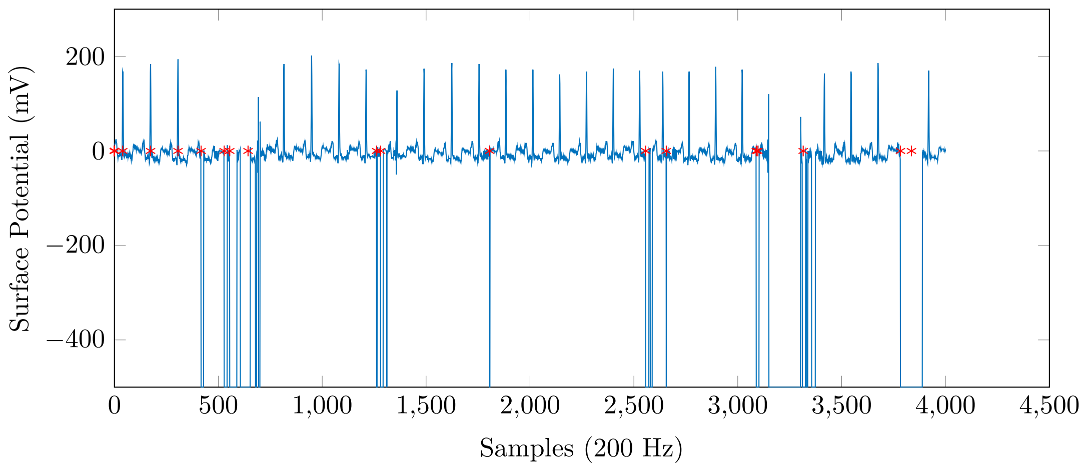
Time	Array1	Array2	Combined
17:52:19	0	0	0
17:52:49	0	0	0
17:53:19	0	1	1
17:53:49	1	1	1
17:54:19	1	1	1
17:54:49	1	1	1
17:55:19	1	1	1
17:55:49	1	1	1
17:56:19	1	1	1
17:56:49	1	0	1
17:57:19	0	0	0
17:57:49	0	-2	0
17:58:19	-2	-2	-2
17:58:49	-2	-2	-2
17:59:19	-2	-2	-2
17:59:49	-2	0	0
18:00:19	1	0	1
18:00:49	1	1	1
18:01:19	0	1	1
18:01:49	0	0	0
18:02:19	0	0	0

2.3.3 Artifacts

A good AF analysis of an ECG based on RR-intervals depends on an accurate detection of R-peaks. A variation on the Pan and Tompkins algorithm was used to find these peaks. This algorithm makes use of a patient specific range based on the minimum and maximal value present in the ECG. All files contain artifacts during which the value of the ECG increases or decreases dramatically. This means that a high presence of artifacts causes this range to be set at a very high level and only the artifacts itself will be detected as R-peaks as can be seen in figure 2.2a.

To make sure artifacts will not affect the results, it is important to filter the data. In this study the ECG files were plotted after which the minimum and maximum of the good quality signal was observed and used as thresholds for the filter. All samples exceeding these thresholds were seen as artifacts and set as 0. The thresholds were manually adjusted for each ECG. The result is shown in figure 2.2b.

(a) Before filtering



(b) After filtering

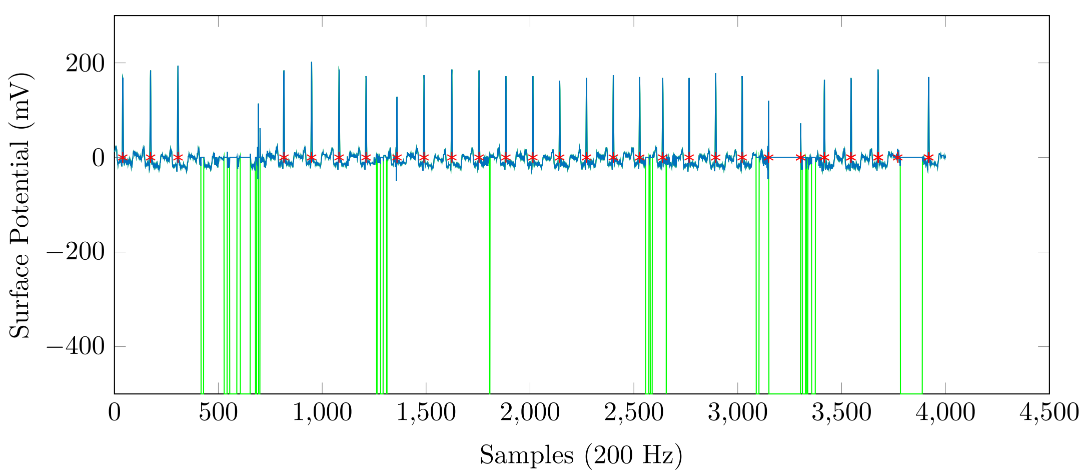


Figure 2.2: The Pan and Tompkins model has been applied to detect R-peak locations (red asterisks) in the blue ECG. In (a) detection of low quality of an unfiltered ECG can be observed. Figure (b) shows the same ECG in green with the filtered ECG in blue and high quality R-peak detection.

2.4 Incidence and burden

The generated text files containing the AF scores, could not yet be used for analysis. Firstly, the starting time of the recordings is incongruent with the time of the end of the surgery, which is the starting time of postoperative day 1. Secondly, files often contained overlap because new recordings were made while other recordings still continued. This overlap needed to be excluded. To overcome these difficulties, and be able to calculate the incidence and burden per day, 24 hours postoperative, the files of the patients were revised. Firstly the files were merged automatically, so one text file per patient was generated. These merged files were then edited manually. Data before the end of surgery was excluded, as well as overlapping data. Finally these files were cut in parts of 24 hours.

To define the burden and incidence, these processed files were then imported in Matlab. Firstly, the periods of which no AF score (-1, -2, and -3) was calculated, were deleted from the list. By doing so, this data was neither taken into account for the total time as well as for the burden time which causes the least information bias. Then the burden and incidence are calculated. The burden is calculated by counting all ones and dividing it by the total time the AF score is recorded. Regarding the incidence, every change from a 0 to a 1 in the list is counted as a new episode and adds up to the incidence of the patient that day. Since the total time differs per day due to the variety in error time or length of recording time, the incidence was normalized by turning it into a ratio of incidence per 24 hours.

2.5 Statistics

Descriptive statistics have been performed on the incidence and burden in order to quantitatively describe the data. The registration time differs per patient per day therefore standard means can be biased. Hence all incidence and burden values are weighted with:

$$Weight = \frac{Registered\ time\ per\ patient}{Total\ registered\ time\ of\ population}$$

This way the burden of a patient with 24 hours of registration weighs three times more in the mean than the burden of a patient of whom 8 hours of registration was available and bias is prevented.

To analyze the variance between the incidence and burden between different days, a univariate general linear model analysis has been conducted in SPSS. This is a technique to analyse the variance for experiments with two or more factors: in this study the two variables and days. In this analysis a pairwise comparison is favourable between the mean of different days.

The general linear model applied is the Tukey Honest Significant Difference Test (Tukey HSD or Tukey), which combines a single step comparison procedure and a statistical test. With no equal sample size over the different days, SPSS automatically implements the Tukey-Kramer test. [27,28] It also assumes equal variation across observations, so repeated observations can be analyzed with this procedure.

The method calculates the studentized range statistic for each pair of days:

$$\frac{Mean\ Day(I) - Mean\ Day(J)}{Standard\ Error}$$

where I and J represent different days. The outcome states if means of different days significantly differ from each other and compares all possible pairs.

To verify whether a correlation could be observed between the incidence and the burden, these variables were visualized in a scatterplot. A quadrant analysis was performed on this scatterplot.

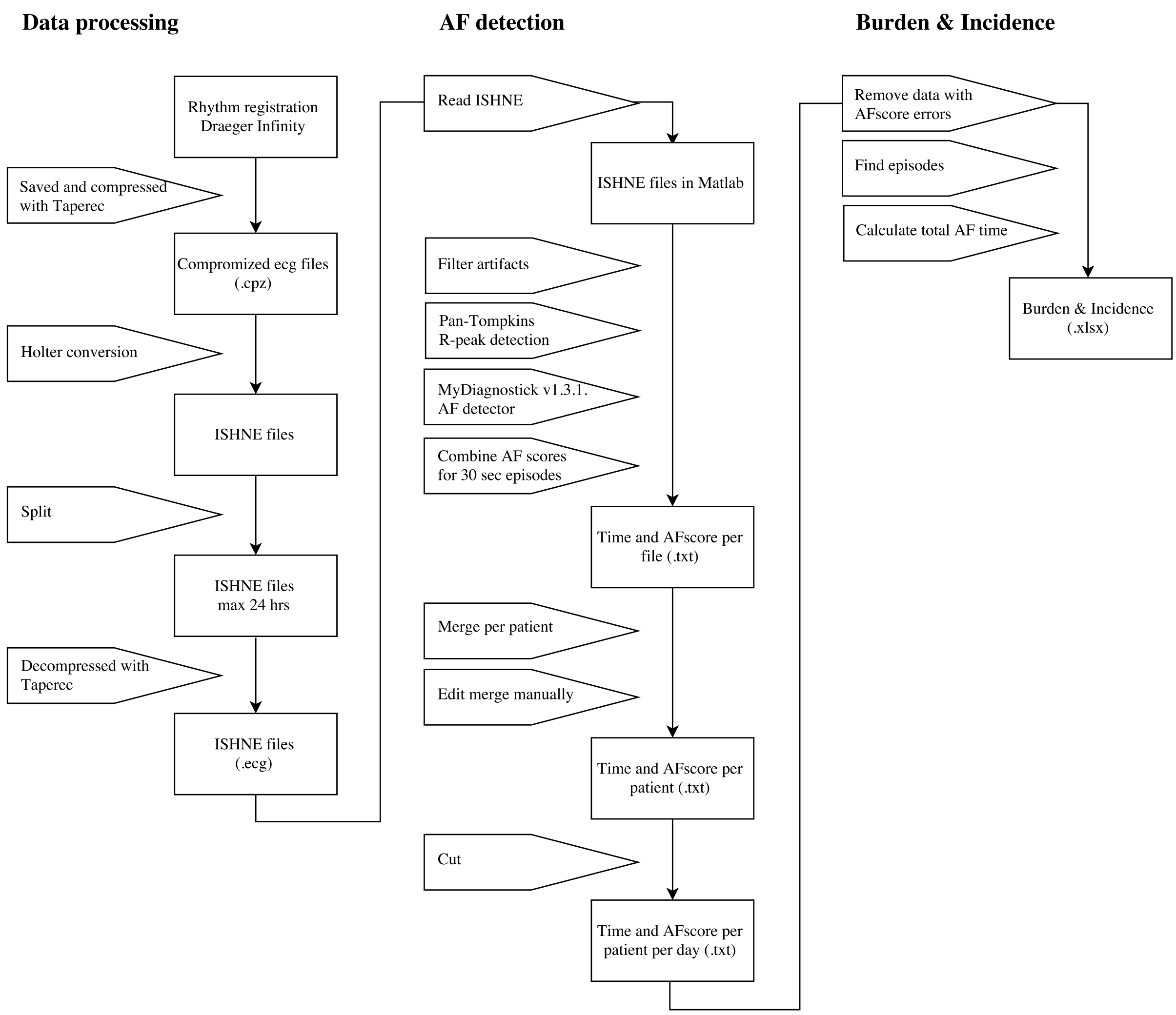


Figure 2.3: This flowchart describes how the data was processed throughout the different phases of the method explained in this chapter.

3

Results

3.1 Validation

In order to validate the used Matlab model, the MIT-BIH Atrial Fibrillation Database has been used. This database contains ECGs, which were analyzed independently by two cardiologists and represent the gold standard. Periods of sinus rhythm were annotated with 'N)' and periods containing AF, annotated with 'AFIB)'. The ECGs were downloaded from the database and loaded into Matlab. The search for periods of AF in five MIT-BIH files of approximately an hour was done as described for our data in the subsections 2.3.1 and 2.3.2. The results of this validation are shown in crosstable 3.1.

Table 3.1: Sensitivity and specificity analysis
The total amount of true and false positive and true and false negative AF periods is shown for five patients extracted from the MIT-BIH database

	AF (MIT)	No AF (MIT)
AF (Matlab)	201	35
No AF (Matlab)	0	434

With these results the sensitivity and specificity of the used method was calculated. The outcomes resulted in a sensitivity of 100% and specificity of 92.5%.

3.2 PoAF incidence and burden

After running a dataset of twenty-one patients, three were excluded, because of a non-existent burden and incidence. An overview of the patients and their weighted incidence and burden over the registered time is shown in figure 3.1 and table 6.1.

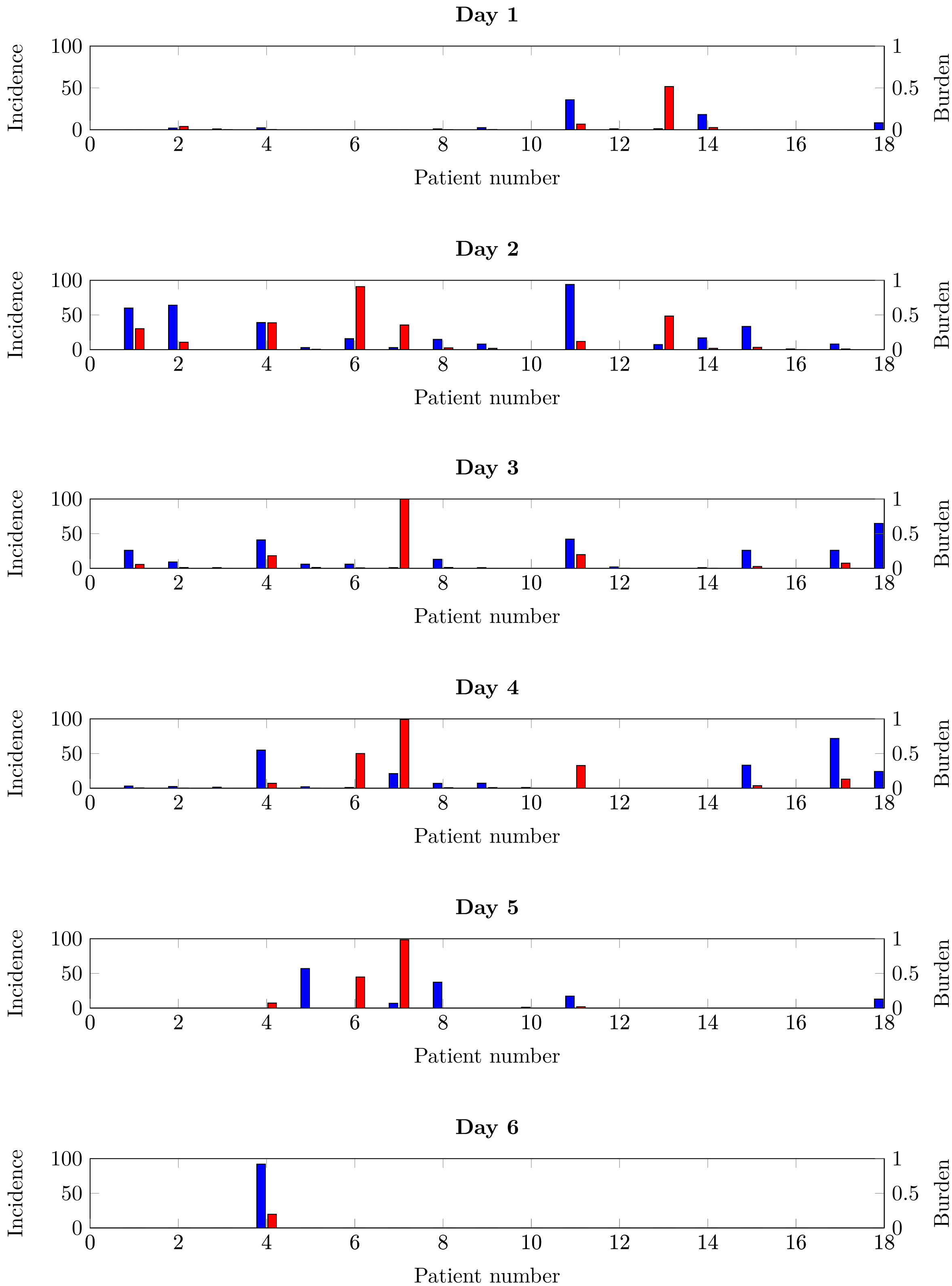
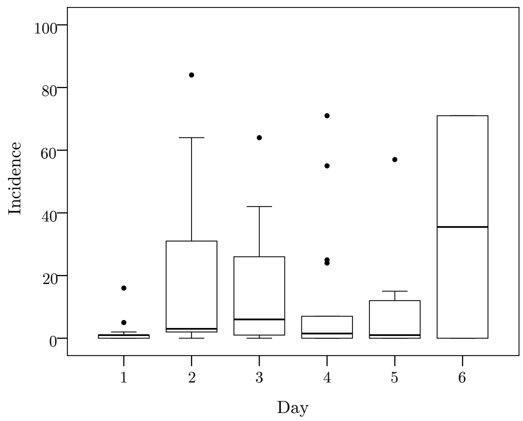
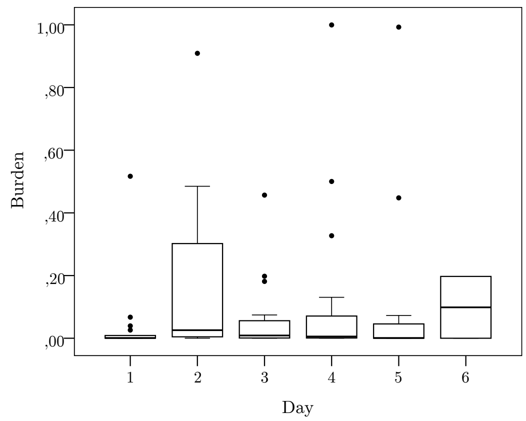


Figure 3.1: Weighted mean incidence *(blue bar)* and burden *(red bar)* of each patient per day.

The boxplots in figure 3.2 show an extensive range in incidence and burden, meaning the data contains many outliers. The median is present in the lower part of the box and lies far apart from the mean. This implies that both incidence and burden are not normally distributed, which is confirmed by the Kolmogorov–Smirnov test. By observing the boxplots it was verified that the data is rightly skewed.



(a) Boxplot incidence



(b) Boxplot burden

Figure 3.2: Boxplots of the outcomes plotted per day which show the data of the incidence (a) and the burden (b). The asterisks are outliers, the box divisions the median.

The data was first analyzed by performing descriptive statistics. Means were calculated introducing a weight factor based on the registration time of the patient contributing to the total registration time of the population. Patients suffering from PoAF after AVR turned out to have a mean incidence of 12.73 ($\pm$12.98) and a mean burden of 0.105 ($\pm$0.168) within the six days after surgery.

Figure 3.3 and 3.4 show the weighted mean and weighted standard error of the incidence and burden per day. The population of the fifth day is smaller, making the results more vulnerable to bias. The sixth day has been excluded from these graphs as the mean was based on only two patients with a total of less than 19 hours of registration.

As can be seen in figure 3.3 the incidence on the second day shows a relatively high mean. The Tukey HSD-test demonstrated no significant difference in incidence between days at a significance level of 0,05. Figure 3.4 indicates a moderate increase in the weighted mean burden over the postoperative days. Neither the difference in burden over different days is significant.

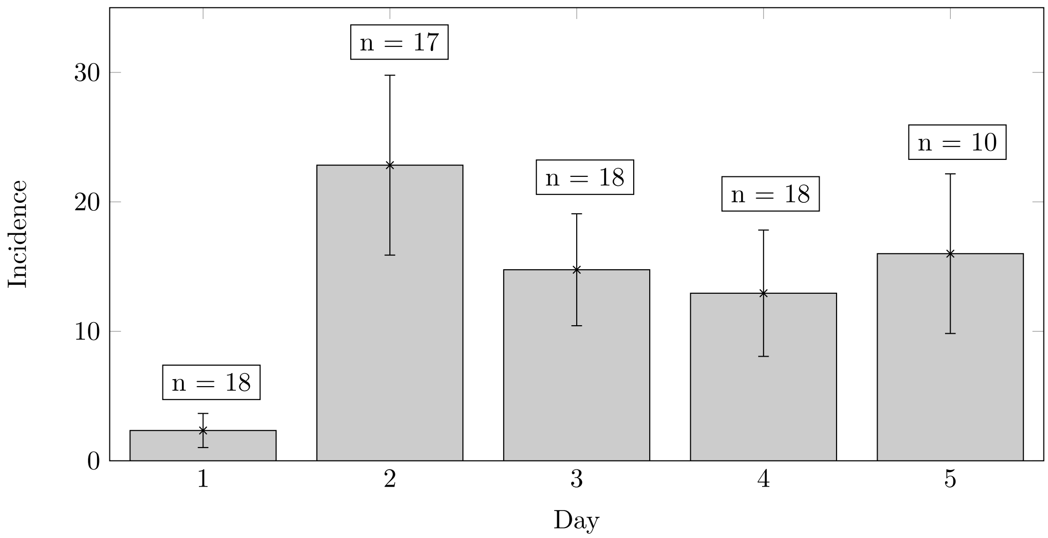


Figure 3.3: Weighted mean incidence of AF episodes of the population is shown for five postoperative days with its weighted standard error. The number of patients of which data was available is noted above each bar.

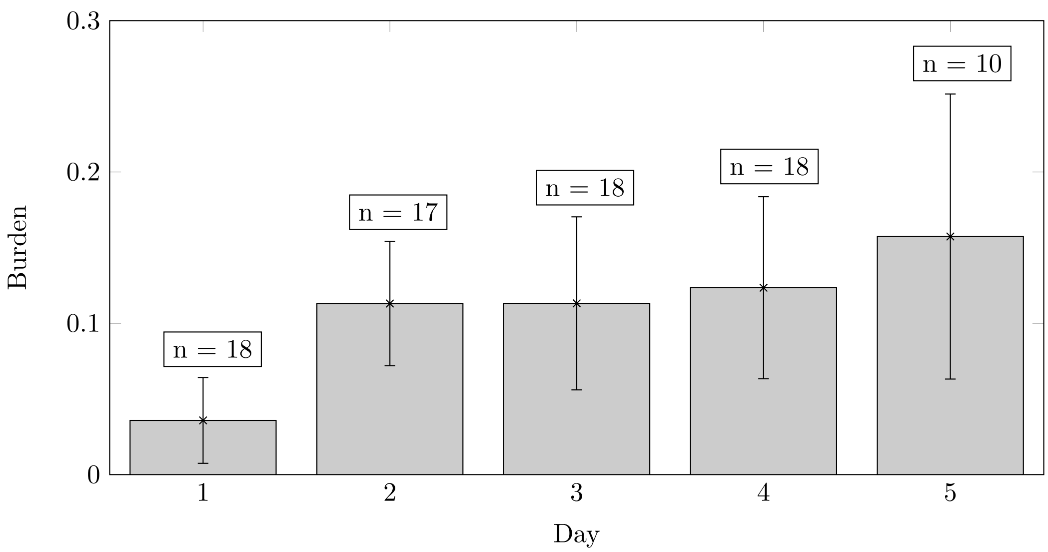


Figure 3.4: Weighted mean burden of AF episodes of the population is shown for five postoperative days with its weighted standard error. The number of patients of which data was available is noted above each bar.

3.3 Relationship between incidence and burden

In the scatterplot (figure 3.5) can be observed that no apparent relation between the distribution of the data points, thus the variables incidence and burden exists. The data points are colored in order to make distinction between different days. From this can be drawn that the points are distributed randomly and independent from the day. Reference lines are drawn within the scatterplot on the mean of the incidence and burden, dividing the plot into quadrants. It is evident that most of the data points lie in the left bottom quadrant. Outliers can be observed in the left upper quadrant as well as in the right upper and bottom quadrant. Because no pattern can be observed in the data points a regression line could not be drawn.

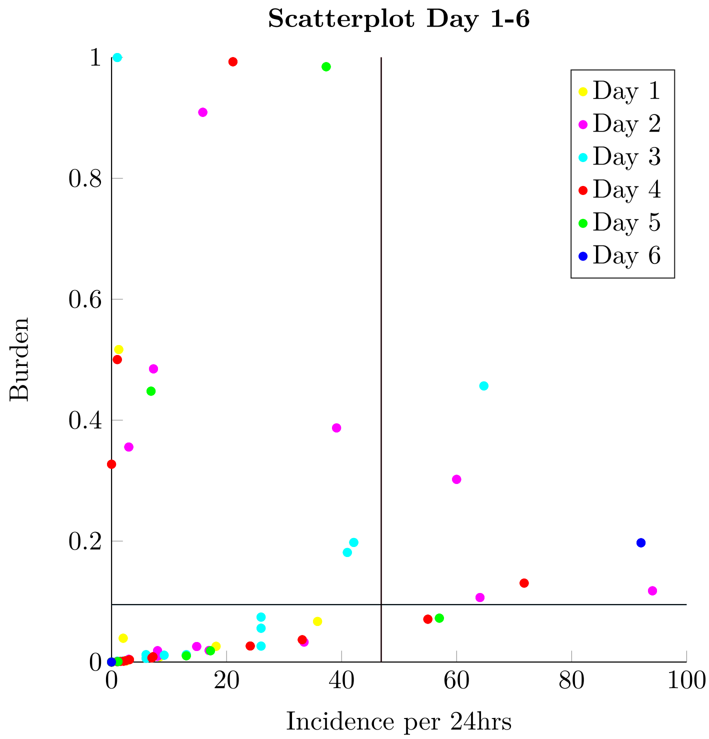


Figure 3.5: Correlation between the incidence and burden for all days. Colors are used to distinguish between different days.

4

Discussion

4.1 Validation method

The used method has been validated with the MIT-BIH database consisting of annotated ECG files representing the gold standard. These example ECGs are short registrations of good quality, in contrast to the dataset analyzed. The method of this study has therefore been validated for good quality ECGs and not necessarily for a dataset containing artifacts and variance between patients. In order to verify the accuracy of the method on coping with these artifacts and variances, the output of this study has been compared to the output of Synescope$^{\mathrm{TM}}$, however this has not been quantified.

4.2 Incomplete data

Due to artifacts and differences in registration time, results were normalized. Despite the normalization, the fact that data is incomplete implies that the actual incidence and burden the patient suffered from could deviate from the results of this study.

4.3 Exclusion of data

After calculation of the burden and incidence it turned out that for three patients the inclusion criteria were not met, since they did not suffer from PoAF. Therefore they were excluded from the population. These patients were part of the dataset received from the EMC, which was supposed to include solely patients that suffered from AF. There are three reasons this difference in AF diagnosis can be attributed to. First of all, when comparing the output of Synescope$^{\mathrm{TM}}$ with the outcome of this study, it was found that Synescope$^{\mathrm{TM}}$ annotated some flatlines of the ECG as AF episodes. Secondly, the AF detected by Synescope$^{\mathrm{TM}}$ was in periods of less than 30 seconds. As AF is defined as a period of AF for a duration of 30 seconds, these short episodes are not detected as AF by this detection program. Last, the ECGs analyzed in this study excluded the part of the ECG registered during surgery. It is possible the patient suffered from AF during surgery and has therefore been included in the dataset of the EMC.

4.4 ECG file size

With a sample frequency of 200Hz for 24 hours per file, we discovered that the processors available to us were not optimal for the necessary analysis of these patient files. Loading these files into Matlab and the detection of R-peaks were time-consuming processes. To make the detection of R-peaks more efficient we tried to filter and resample the signal in Matlab. It is important to filter the signal before resampling in case there is high frequent noise within the signal, since this can disturb the signal if resampled. Calculation showed that a frequency of 25Hz should be sufficient to detect all R-peaks. Taking aliasing into account, a frequency of 50Hz was chosen to perform a trial on. One ECG file was filtered and resampled to compare the running time and quality of output of R-peak detection with the original sample frequency of 200Hz. The processing time was not much shorter and the detection of R-peaks was less accurate. By doing the alteration this way the downsampling takes place after the ECG files have been loaded into Matlab. Yet this was a time-consuming process as well. Alternatively the process can be fasten by saving the ECG signal on a lower sample frequency. This way, the time of loading the files will already be reduced. This method is only useful though if accurate R-peak detection can still be guaranteed.

4.5 Overlapping data

The ECG files contained inconsequent registration overlap. Currently the ECG files in the EMC are saved containing a period of maximal 72 hours. However, before this maximum registration time is reached, the next ECG recording is started, while the earlier registration continues to be saved. Therefore many of the files overlap. To automate proper overlap removal is not easy, thus this has now been done manually. It is recommended to change the way data is saved. The usage and processing of the data would be easier and more efficient if the ECG recordings would be saved automatically after a fixed period of time. Every ECG file would start at the time the previous file ended with and this would prevent the overlap of data. The merging and cutting of the files would then no longer be relevant which would save manual work and time.

4.6 Artifact filtering and R-peak detection

For accurate R-peak detection it is necessary to filter artifacts as explained in the Method. In this study the thresholds for the filter were manually adjusted. For larger populations it would be favourable to automate this step. A fourier transformation has been performed to find the specific artifact frequency. A lowpass filter and high pass filter were applied to try to filter the artifacts, however this did not provide a solution. Additionally the overall mean of the signal is being influenced too much by the artifacts to use as a factor for calculating thresholds. A solution was found whereby six periods of 10 seconds are taken from the ECG file from which the minimum and maximum value are saved in an array. Extreme values are excluded whereupon the average of these minimum and maximum values is calculated and used to determine the threshold. This has not yet been implemented in this study, but the method has been created and can be found in the Appendix 6.2 .

5

Conclusion

The automatic detection method has provided new insight in the two variables burden and incidence and their possible correlation. In the recent years only the incidence has been used to quantify PoAF. But as the burden does not follow the same pattern as the incidence it might be a better variable to define PoAF severity. As described in the introduction, AF can cause cardiac remodeling and longer episodes seem to have a greater effect. [21] Taking this into account, the burden could be a more reliable factor in the description of the correlation between AF, complications and prognoses. To verify this, research on the burden on a larger population is recommended. To verify this, research on the burden on a larger population is recommended.

At the moment, research is being done at the EMC to find out more about the origin of PoAF. During surgery, mapping registrations are being performed. These registrations are supposed to be a predictor for the development of PoAF. Automatic AF detection can be used to facilitate validation of these results. Automatic detection of PoAF makes it easier to generate the values of incidence and burden and can therefore be used to learn more about the correlation between these variables and certain cardiovascular complications. When the method is optimalized, incidence and burden can be included in the medical status of every patient and contribute to further research.

This research focused on the average burden per patient per day. Not only the average burden per day, but also the variation in length of the episode may provide important information about the chance of cardiac remodeling and the recurrence of AF.

The automatic detection method enables the detection of single PoAF episodes. This can be used in further research in order to explore the potential influence of hemodynamic fluctuations on the occurrence of such an AF episode. During an earlier phase of this research a method has been designed to investigate this correlation.

Correlations between PoAF burden and predictive and prognostic factors can be found by performing this further research and will provide additional information on parameters regarding the origin and occurrence of AF.

6

Appendix

6.1 Population

Table 6.1: Patient Population
The patient population (n=18) which suffered from PoAF is described with the total registration time, the incidence, the relative incidence and total burden and relative burden detected during this time.

*Total time is described as the time registrations were available from the end of surgery excluding the time errors occurred.

Patient nr. n=18	**Gender m=12 f=6**	**Total time* (hrs)**	**Total Incidence**	**Relative Incidence (per 24 hrs)**	**Total Burden (hrs)**	**Relative Burden (%)**
Pt 005	m	71:20:30	31	10	1:40:30	2.35
Pt 006	f	90:49:30	77	20	3:48:00	4.18
Pt 013	f	87:31:00	3	1	0:03:30	0.07
Pt 015	m	107:27:00	159	36	15:11:30	14.14
Pt 017	f	92:08:00	11	3	0:26:00	0.47
Pt 018	m	94:51:00	15	4	24:15:00	25.57
Pt 021	m	109:23:30	66	14	73:19:30	67.03
Pt 041	m	85:22:30	23	6	0:33:30	0.65
Pt 044	f	77:22:30	16	5	0:39:30	0.85
Pt 072	f	90:55:00	2	1	0:02:00	0.04
Pt 077	m	89:49:00	133	36	15:22:00	17.11
Pt 085	m	90:59:30	3	1	0:03:30	0.06
Pt 086	m	90:32:30	3	1	13:04:30	14.44
Pt 087	m	82:50:30	25	7	0:48:00	0.97
Pt 089	f	70:38:00	83	28	2:02:00	2.88
Pt 093	m	91:00:00	1	0	0:01:00	0.02
Pt 094	m	90:41:30	105	28	5:06:30	5.63
Pt 104	m	77:38:00	104	32	11:46:00	15.16
Mean		88:24:25	48	13	9:20:42	9.53
Standard deviation		10:14:14	51	13	17:31:12	16.28
Standard error			12	3.1	4:07:46	3.84

6.2 Overview Matlab scripts

Table 6.2: Matlab scripts
A contents list of the different Matlab scripts made and used for this study. The input is the filetype needed to run the script and the output is what is generated after running the script. The column 'Functions needed' describes the additional functions that should be included in the path to enable the running.

Functionality	Input	Output	Functions needed
1. R_peak_detection.m			
This script will load the ECGs from a specified path read them using the function 'read_ishne' and detect the R-peak using the fucntion 'pantompkins'. The output will be saved in the structure R on the specified path.	ISHNE-file	Structure R containing information about the R-peak	read_ishne, pantompkins
2. R_peak_detection_with_auto_threshold.m			
This script does the same as *R_peak_detection.m*, but automatically calculates the thresholds for the artifact filter.	ISHNE-file	Structure R containing information about the R-peak	read_ishne, pantompkins
3. AFscore_calculation.m			
This script starts with reading a part of the ISHNE files so the information needed can be read from the header. Afterwards the AFscore is calculated per minute starting at t=0 s and also starting at t=30 s. These are combined in a table so an AFscore per 30 seconds is generated.	ISHNE file and accompanying structure containing the R-peaks	A table containing an AFscore per 30 seconds	subdir, read_ishne, afdet.mexw64
4. Merging_AFscores.m			
This script was used to merge the different files containg AFscores to one file, to be able to cut them up in days afterwards.	Different files of AFscores of one patient	One text file containing all the AFscores of one patient	subdir
5. Cutting_AFscores.m			
This script can be used to cut the merged files for each patient into file of 1440 lines representing 24 hours.	AF score text file per patient	Text file of AF score per 24 hours	None

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