Exploring Alternans Characteristics of Electrocardiogram for Prediction of Paroxysmal Atrial Fibrillation

by

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Bachelor of Science, Computer Engineering
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Submitted to the Department of Electrical Engineering and Computer Science
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To my parents, Amin and Rashida,
my brother Adeel, and my
lovely sisters, Abeer and Maryam.

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Abstract

The goal of our thesis was to investigate if P-wave and PQ segment alternans can be used to detect and predict Paroxysmal Atrial Fibrillation (PAF) from an Electrocardiogram (ECG). The work involved implementing an algorithm for computing alternans information for a region of ECG, applying the algorithm to derive P-wave and PQ segment alternans information, and analyzing data generated for normal and PAF ECGs for evidence of any distinguishable predictive characteristics. Based on analysis of total 80 patient records (35 normal and 45 PAF) with validation on 30 records randomly selected from those (achieving c-indexes between 0.66 and 0.70), we concluded that alternans can potentially be a useful predictor for PAF.

Thesis Supervisor: Richard Cohen
Title: Professor, Harvard-MIT Division of Health Sciences and Technology

Acknowledgments

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Chapter 1

Introduction

The goal of our thesis was to develop and evaluate an Electrocardiogram (ECG) based predictor of Paroxysmal Atrial Fibrillation (PAF).

PAF is an abnormal heart beat condition that is widely prevalent. A reliable predictor that can identify people at risk for or having PAF is of vital importance. Such a predictor does not exist at the moment.

We propose, implement and investigate a novel predictor for PAF based on P-wave and PQ segment alternans. The encouraging results suggest that alternans may be a possible predictor and the model developed needs to be tested on further data to validate its use.

1.1 Organization of the Thesis

In the following chapter, a brief description of the abnormal heart beat condition (or arrhythmia) called Paroxysmal Atrial Fibrillation (PAF) is given, followed by the significance of reliable predictors of the condition, an overview of past attempts at devising a predictor, and finally some motivation for our investigation.

Chapter 3 provides a detailed description of the system implemented for the computation of accurate, reliable and robust measure of alternation within an ECG signal, which is the basis of our predictor.

Chapter 4 describes the techniques used to analyze the information generated by

applying the system developed to an ECG database of normal and PAF patients.

Chapter 5 presents the results produced by our investigation and an evaluation of the performance of the predictor.

Finally, Chapter 6 derives appropriate conclusions based on these results and makes recommendations for future work.

Chapter 2

Background

We start with the heart of our problem.

2.1 The Heart

The heart is a muscular organ that pumps blood continuously to the rest of the body through the circulatory system. The pumping action of the heart is achieved through a regular sequence of electrical impulses that move through the heart in a particular pattern. As long as the electrical impulse is transmitted normally, the heart pumps and beats at a regular pace. A normal heart beats 60 to 100 times a minute. Normal heart rhythm is termed sinus rhythm.

An **arrhythmia** is a change from the normal sequence of electrical impulses, causing abnormal heart rhythms. This can cause the heart to pump less effectively. Some arrhythmias are so brief (for example, a temporary pause or premature beat) that the overall heart rate or rhythm is not greatly affected. But if arrhythmias last for some time, they may cause the heart rate to be too slow or too fast or the heart rhythm to be erratic.

In the condition called **atrial fibrillation** (AF), many parts of the atria, the heart's two upper chambers, start emitting uncoordinated electrical signals. The atria pump too fast and unevenly and do not fully contract. In fact, they may contract 57 times faster than normal – up to 300-400 beats per minute. Not all these signals

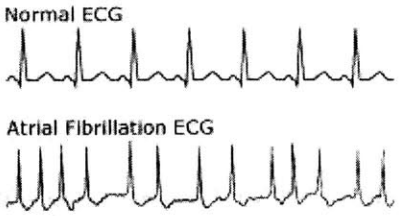

Figure 2-1: Normal ECG vs Atrial Fibrillation ECG

go to the ventricles (the two lower chambers of the heart), so although their rate is irregular, it is not too fast and the ventricles can still pump out blood.

An estimated 2.2 million Americans are living with AF [1, 2]. That makes it the most common"serious" heart rhythm abnormality. The prevalence of AF increases with age [1, 2].

2.2 Paroxysmal Atrial Fibrillation

Atrial fibrillation (AF) can be sustained or paroxysmal; in sustained AF, the rhythm is permanently abnormal, while in paroxysmal AF, there are intermittent periods of AF that usually terminate spontaneously. For both these types of conditions, it is important to be diagnosed early.

2.2.1 Electrocardiogram

A surface electrocardiogram (ECG) monitors the electrical activity of the heart. It is used extensively and universally to investigate heart disease. An ECG recording would reflect the incidence of AF rhythm while it is happening, as shown in Figure 2-1, and AF can be detected visually from the ECG by doctors or detected automatically by a computer. In AF, the atria (upper chambers of the heart) contract rapidly and irregularly and this is reflected in the P-wave portion of the ECG and the variation in the beat rate. The parts of a typical ECG signal are shown in Figure 2-2.

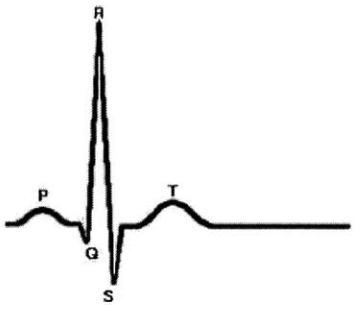

Figure 2-2: Parts of a typical ECG. P-wave: Depolarization of atria. QRS: Depolarization of ventricles. T-wave: Repolarization of ventricles.

2.3 Need for PAF Predictor

AF is associated with significant morbidity. Even though AF is not life-threatening, it may severely impact the quality of life. It can lead to other rhythm problems, chronic fatigue, congestive heart failure and worst of all — stroke. When the left atrium pumps too fast and unevenly, blood does not empty completely into the left ventricle (resulting in decreased cardiac output). Instead, leftover blood "pools" in the atrium. This blood can form clots. If a clot breaks loose, enters the bloodstream and travels to the brain, it can plug an artery and cause a stroke. This does not happen to everyone with AF, but chances of having a stroke are five times higher for a person with AF. About 15-20 percent of all strokes occur in people with AF [2].

In some cases, AF is asymptomatic. In others, an irregularity is noticed such as sensations that include a racing, uncomfortable, irregular heartbeat and a "flopping" in the chest. Dizziness, sweating and chest pain or pressure also can occur. Other symptoms include difficulty breathing, a feeling of overall weakness and being unable to exercise.

The difficulty with diagnosing Paroxysmal or intermittent AF lies in the fact that it may not always show up in the ECG, depending on how rare or frequent the AF beats are. During the periods of normal sinus rhythm (i.e. when the AF is not happening), the ECG may look the same to the naked eye as that of a normal person.

A predictor that could tell if a normal sinus rhythm ECG belonged to a person

with PAF (or someone at risk for AF) would be quite useful for several reasons: ECG measurement is non-invasive and convenient; treatment can be given to manage PAF once it is diagnosed; and the acute onset of AF can be prevented using pacing [3, 4, 5], drug management or defibrillation techniques [6]. The risk of stroke can be reduced by administering antiarrhythmics and anticoagulants. Often PAF degenerates into sustained AF (30% of cases [7]) and the maintenance of sinus rhythm may reduce the susceptibility to future episodes of PAF, while decreasing symptoms and improving hemodynamics [8].

2.4 Previous work

Currently, reliable methods do not exist for identification of patients with Paroxysmal Atrial Fibrillation from ECG that does not include any episodes of Atrial Fibrillation. However, methods and algorithms have been implemented that produce encouraging results (in terms of sensitivity and specificity) and indicate that it may be possible to perform a reliable identification based on ECG.

Based on the literature survey carried out by the author on various attempts made to approach this problem, the following sections summarize the aspects and features of ECG that have been investigated for their predictive ability.

2.4.1 Time domain analysis

Time domain analysis has been done on the P-wave portion of the ECG. The P-wave corresponds to electrical activity generated by the depolarization of the atria. The atria pump blood into the ventricles (which pump blood to the rest of the body). The mechanical contractions of the heart chambers are produced by a continuous cycle of depolarizations and repolarizations [1] of individual cells in the heart. There is no distinctly visible wave representing atrial repolarization in the ECG because it occurs during ventricular depolarization. Because the wave of atrial repolarization is

[1] in simple terms, depolarizations and repolarizations are chemical processes that occur in muscle cells and thereby cause propagation of electric impulses resulting in mechanical contractions and relaxations

relatively small in amplitude (i.e. has low voltage), it is masked by the much larger ventricular-generated QRS complex.

The P-wave has been investigated for changes and differences in the case of patients with PAF compared to normal patients. The following are most of the P-wave time domain measures that have been analyzed and shown to be indicative of AF to some extent:

- Prolonged P-wave duration [9, 10]
- Signal-averaged P-wave duration: The P-wave is averaged over a number of beats and the length is measured on the average. [11, 12, 13]
- P-wave dispersion: This is the difference between the maximum and the minimum P-wave duration detected in a 12-lead standard ECG. [14]
- P-wave duration variance [15]
- Prolonged PR interval [16]
- Atrial late potentials: The later part of the P-wave has been analyzed and in AF patients, the terminal portion has been found to be lower in amplitude and duration than it is in normal subjects [13].

2.4.2 Frequency domain analysis

Frequency domain analysis techniques have not yielded indexes as useful as those obtained by time domain analysis. However, since these methods do not require the accurate localization of P-wave onset and offset, they may overcome the limitations suffered by time domain techniques. Frequency techniques have included the spectrum analysis of the P-wave [17, 18].

2.4.3 Premature complexes detection

Premature atrial complexes (PACs) have been found to have a significant correlation with PAF. Kolb et al. analyzed 297 spontaneous episodes of AF in 33 patients and

found that PACs initiated 93% of them [19]. A PAC is a sudden reduction in the beat interval length, followed by a beat of normal length. The frequency of occurrence of PACs has been found to increase prior to AF onset.

At the 2001 Computers in Cardiology challenge, which was to develop a reliable predictor for the onset of PAF, a number of works were presented that showed some correlation between PAC rate and onset of AF [20, 21].

2.4.4 Heart rate variability based analysis

This includes analysis of beat interval lengths such as variation over time. Several features have been investigated such as the power spectral density of the RR interval series, time domain measures such as standard deviation of RR series, and hidden markov modeling and entropy of RR series [20, 22].

Various combinations of the above methods have also been used. Some techniques have used time domain features derived from the P-wave as well as properties such as shape of the P-wave [23].

A detailed review of methods and algorithms implemented for prediction of PAF is available in the publication of Poli et al [24]. Even though considerable progresses have been made recently in AF prediction, no reliable method has been proposed yet. Also, even though the techniques mentioned have shown high predictive values, most of the discriminating tests are not reproducible when performed under similar conditions, except signal averaged P-wave duration. This is due to the considerable changes in the P-wave morphology and RR series with time.

The following section presents the motivation behind the prediction technique proposed, implemented and investigated in detail in our thesis.

2.5 Motivation for Alternans based predictor

In an ECG, the observance of time variations in the morphology of specific regions has been linked to various forms of cardiac instability. In the last decade, T-wave

alternans has been used to predict susceptibility to ventricular arrhythmias [25] and has been shown to be indicative of cardiac electrical instability in general [26].

We propose investigating the use of P-wave and PQ segment alternans as a possible predictor for PAF. The P-wave and PQ segment of the ECG reflect the electrical activity that results in the contraction of the atria. Alternans measurement is a frequency domain method that quantifies the alternations in a waveform segment over time. P-wave and PQ segment alternans, therefore, describe the alternations in the electrical activity of the atria.

We hypothesize that in PAF, the degree of alternations is significantly higher than in normal functioning of the atria. The physiological explanation of this is beyond the scope of this thesis. To test this hypothesis, we implemented an algorithm for computing P-wave and PQ segment alternans and applied it on clinical data. We have available a database of PAF and normal ECG signals, acquired from an online physiologic signals resource provided by PhysioNet [27]. These signals are 2-channel Holter ECG recordings. Alternans data was generated and then analyzed for its predictive ability.

Chapter 3

Methods

This chapter describes the implementation of the system developed in this thesis for processing an ECG signal and characterizing beat-to-beat variations in the waveform. A general alternans algorithm is given, followed by the various stages implemented in the process, which are summarized at the end of the chapter in Figure 3-21.

3.1 Alternans Algorithm

In this section, we will describe the algorithm that is used to quantify the degree of alternations in a signal or segment of a signal that is periodic over time. In the sections that follow, we will describe how we used this algorithm and applied it to our problem to quantify the alternations in the P-wave region and the PQ baseline segment of the ECG.

The algorithm will be elucidated with the help of examples of two waveforms: one with alternans and one without. Figure 3-1 is a waveform in which consecutive P-waves from an ECG signal have been adjoined and a periodic signal of P-waves is created. This signal has alternans, that is a significant number of alternations on a beat-to-beat basis. The alternations are visible as up-and-down fluctuations of the peak of the P-wave every other beat. Figure 3-2 shows another waveform of periodic P-waves which does not have significant alternans. Both figures are zoomed in versions of 128 beat segments to which the alternans algorithm was applied.

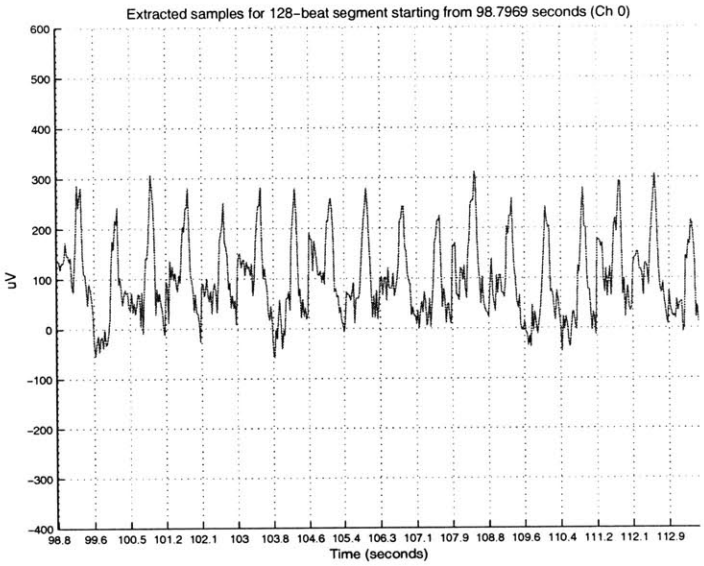

Figure 3-1: A periodic signal with alternans (P-waves of ECG)

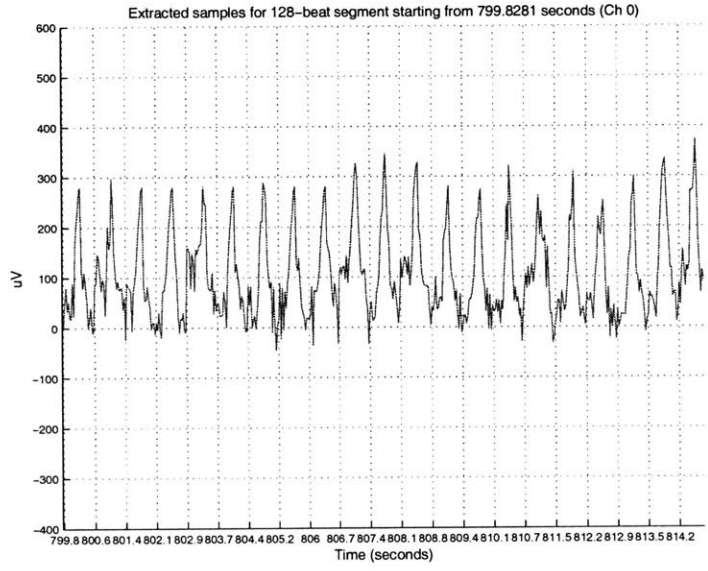

Figure 3-2: A periodic signal with no significant alternans, that is beat to beat alternations (P-waves of ECG)

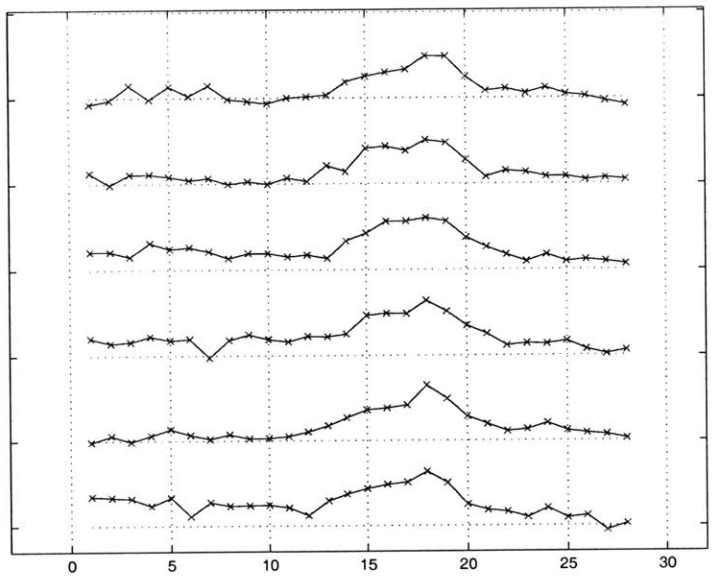

Figure 3-3: A few successive P-waves on top of each other

The first step in the algorithm is to create a matrix in which each column has consecutive samples from one beat. The number of rows is the number of samples in one beat, and the number of columns is the number of beats. We used 128 beats for our analysis which is about 2 minute long measurement, depending on the heart beat rate. This number has been used in the past effectively for T-wave alternans measurement [25, 26].

Figures 3-3 shows a few P-waves from successive beats stacked on top of each other and Figure 3-4 shows variations of each point in the P-wave over time. From Figure 3-4, we can see the fluctuations of individual points in the P-wave over time clearly.

Next the power spectral density (PSD) is calculated for each row (ie across each column). PSD is computed in two steps as follows:

$$X[n] = \sum_{n=0}^{N-1} x[n] e^{\frac{-j2\pi kn}{N}} \qquad (k = 0, \ldots, N-1)$$

$$P[k] = \frac{|X[k]|^2}{N^2} \qquad (k = 0, \ldots, N-1)$$

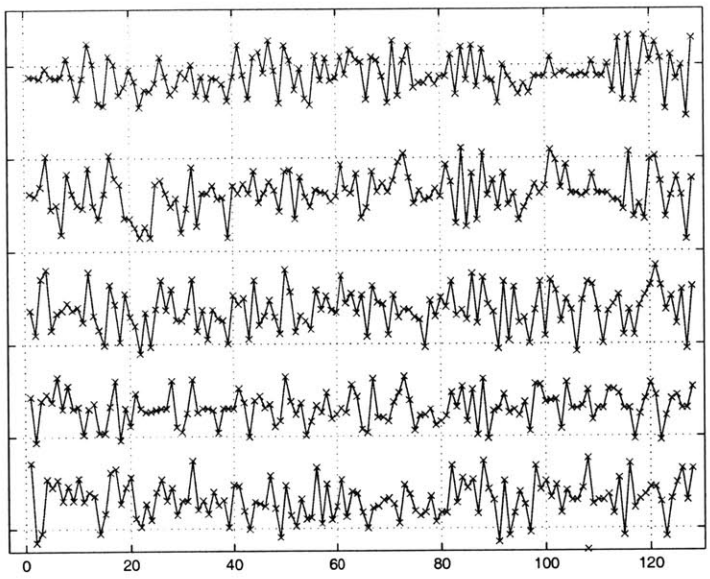

Figure 3-4: Variation of a few samples of P-wave over 128 beats, showing significant beat-to-beat alternations

PSD is basically the square of the magnitude of the discrete fourier transform (for which we used the fast fourier transform algorithm and a length of 128), divided by the length of the signal squared.

For each row, this gives us the PSD of particular points in the signal across all beats, that is a measure of the frequency content of a particular point in the signal. If this is done for all rows, we get the frequency contents of different points in the signal. Since we want a measure of the alternations throughout the signal over time, we compute the PSD for all rows and average them.

The power spectral density for a waveform with alternans should consist of a peak at half the discrete fourier transform (DFT) length frequency ($k = 64$ or cycles/beat $f = 0.5$).

Figure 3-5 shows the PSD obtained for the 128 beat waveform consisting of adjoined P-waves with alternans (Figure 3-1). A peak is visible at $f = 0.5$, which is high relative to the content at slightly lower frequencies.

Figure 3-6 shows the PSD obtained for the 128 beat waveform without alternans (Figure 3-2). In this PSD graph, there is no peak at $f = 0.5$.

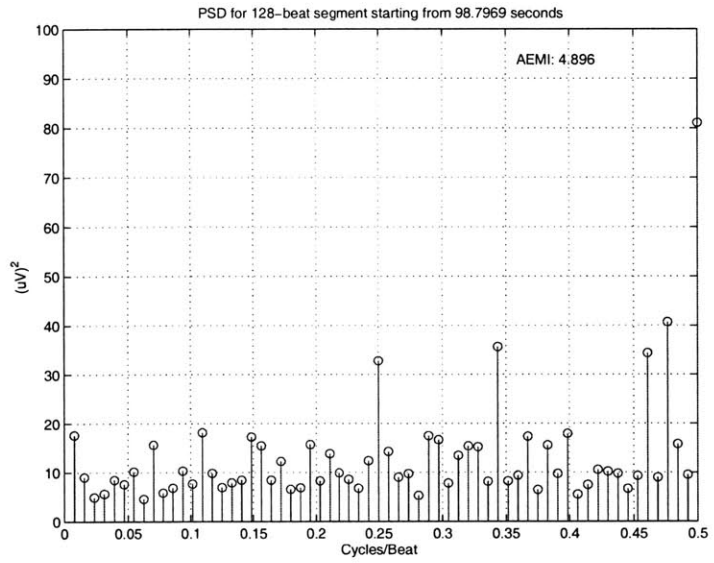

Figure 3-5: Power Spectral Density of alternans waveform in Figure 3-1

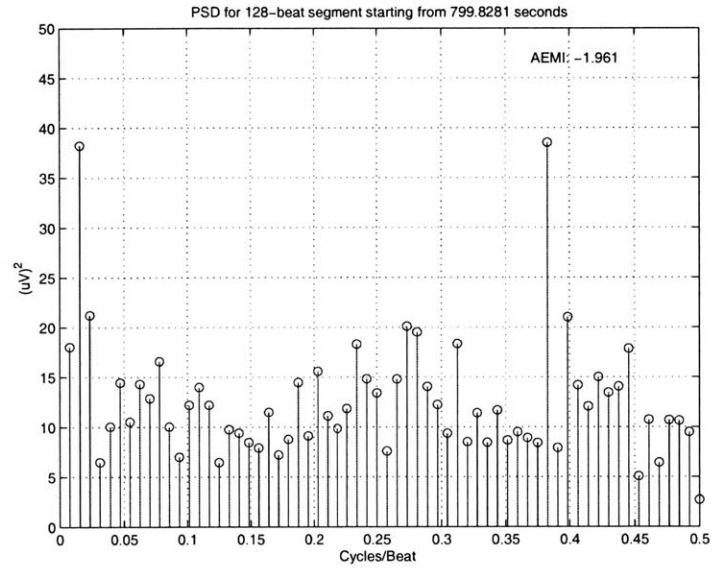

Figure 3-6: Power Spectral Density of non-alternans waveform in Figure 3-2

To quantify our measurement of alternans, we define the following measures:

$$Noise\ Level\ (\eta) = mean(P[k = 56]\ to\ P[k = 63])$$

$$Alternans\ Voltage\ (AV) = \sqrt{P[k = 64] - \eta} \tag{3.1}$$

$$Alternans\ Ratio\ (AR) = \frac{(AV)^2}{standard\ deviation(P[k=56]\ to\ P[k=63])}$$

where $P[k = 56]$ *to* $P[k = 63]$ is our arbitrary definition of the 'noise window' of the PSD [1] and $P[k = 64]$ is the PSD magnitude at half the DFT length.

Alternans is arbitrarily considered 'significant' when the alternans ratio (AR) is greater than 3. This means that the PSD at half DFT length frequency minus the mean of the noise window is three times greater than the standard deviation of the noise window.

The computed values for the two examples we have used are shown in Table 3.1. When the PSD at half DFT length frequency is less than the mean of the noise window, we arbitrarily equate it to zero, to avoid taking the square root of a negative number; plus relative to the noise level, the alternans voltage is in fact zero.

	Alternans voltage	Noise level	AR
Waveform with Alternans	8.01	4.11	4.90
Waveform without Alternans	0	3.26	-1.96

Table 3.1: Alternans values for example waveforms

Since the time waveforms shown in Figures 3-1 and 3-2 are zoomed in versions that do not show all 128 beats, the time variations of individual points in each of the two example waveforms are shown in Figures 3-7 and 3-8. These figures indicate the difference in beat-to-beat fluctuations of individual points in the P-wave for the two example waveforms.

We proceed with the description of how we applied the alternans algorithm to our problem and the methods employed in this thesis to analyze the morphology of the

[1] these are the frequencies or cycles/beat f of 0.44 Hz to 0.49 Hz

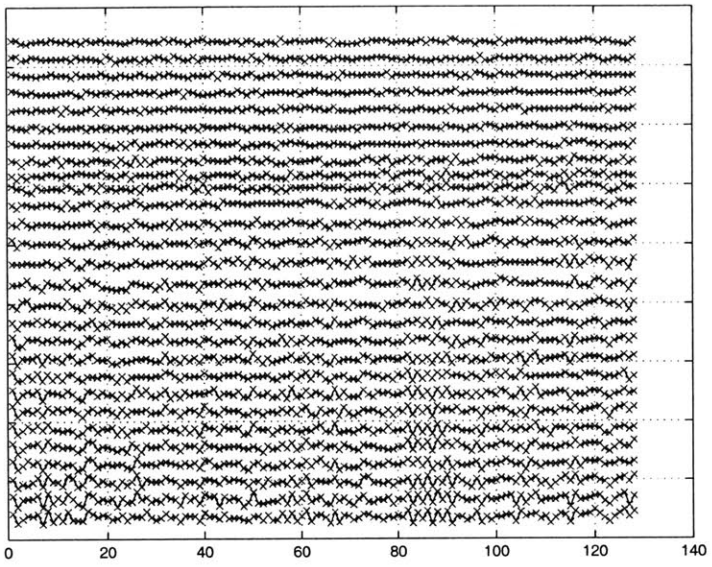

Figure 3-7: Variation of a P-wave's samples over 128 beats for alternans waveform example

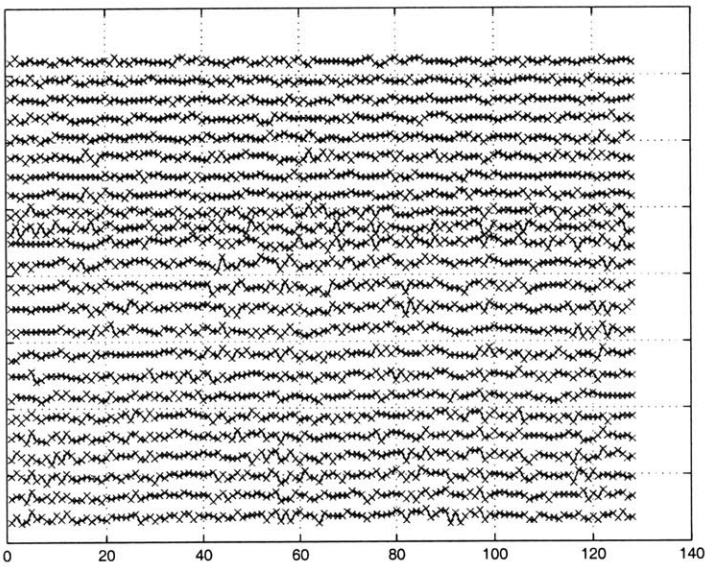

Figure 3-8: Variation of a P-wave's samples over 128 beats for non-alternans waveform example

P-wave and the PQ baseline.

3.2 Preprocessing

The ECG data we had available was produced from Holter device recordings. The ECG is 2 channel and sampled at 128 Hz. The data is not as accurate (i.e. non-noisy) or high resolution as 12-lead bedside ECG monitoring. This thesis is limited to the analysis of alternans on such data. Future work entails applying the alternans analysis software developed in this thesis to more accurate data. The techniques developed in this thesis are easily and readily applicable to other forms of ECG.

In order to minimize the effect of noise on the analysis, some preprocessing is involved prior to the automated analysis algorithm. Noise in Holter ECG comes from various sources such as movement of the leads due to subject movement, skeletal muscle activity, high frequency electrical noise, and breathing (low frequency). As we can see, the noise is both regular (periodic) and irregular (ie spontaneous). Methods follow that attempt to remove both kinds of noise as much as possible (following subsections and section 3.4).

In an ECG, most of the clinically relevant energy falls between 0.05 Hz and 50 Hz. This fact is used when designing the filters to maximize the resulting signal-to-noise ratio.

3.2.1 Low Pass Filtering

A 128-order digital FIR (finite impulse response) filter with a cut-off frequency of 50 Hz was used. The filter impulse response is real and has linear phase. The normalized gain of the filter at the cut-off frequency 50 Hz is -6 dB. A hamming window of length 129 was used to window the impulse response. The magnitude of the pass band is 1 after scaling. Matlab's (version 6.5) `fir1` command was used to implement the filter. The linear phase causes a delay of 64 samples or 0.5 seconds, which is insignificant compared to the ECG signal length of 30 minutes.

The following Figures (3-9 and 3-10) show a segment of ECG before and after high

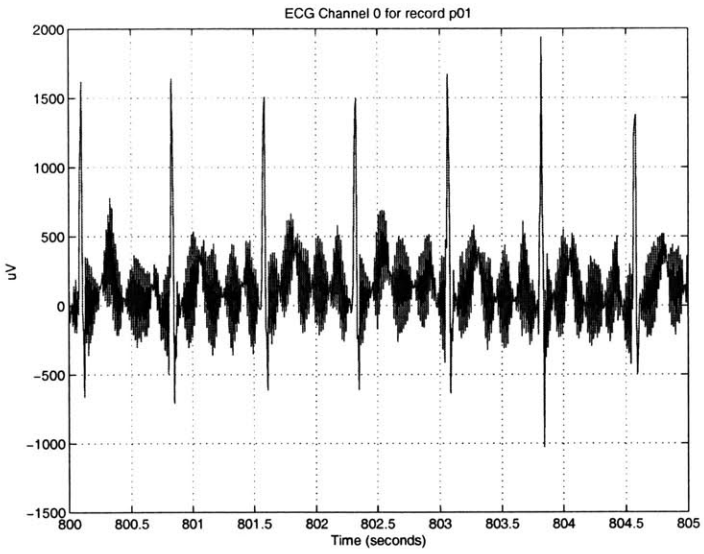

Figure 3-9: Segment of ECG with high frequency noise

frequency noise is removed. It is particularly important to remove high frequency noise for the purpose of alternans analysis as high frequency elements are aliased onto low frequency beat-to-beat variations when segments of the ECG (such as the P-wave) are sampled for every beat. The high frequency noise should not affect inherently existing alternations by subduing them or show up as falsely detected alternans.

3.2.2 Baseline correction for P-wave alternans measurement

Baseline correction is performed as part of preprocessing for P-wave alternans measurement. Often the baseline of the ECG is not aligned at the zero voltage level due to low frequency noise. This procedures aligns every beat of the ECG so that the PQ segment of every beat touches or passes through the zero voltage level. Figure 3-11 demonstrates how this is done. First, the average value of all the points in the baseline is computed for each beat. In the ideal case, this should be zero volts. To perform baseline alignment, the midpoint of the baseline of each beat is shifted up or down by the average baseline voltage so that it assumes the zero voltage level.

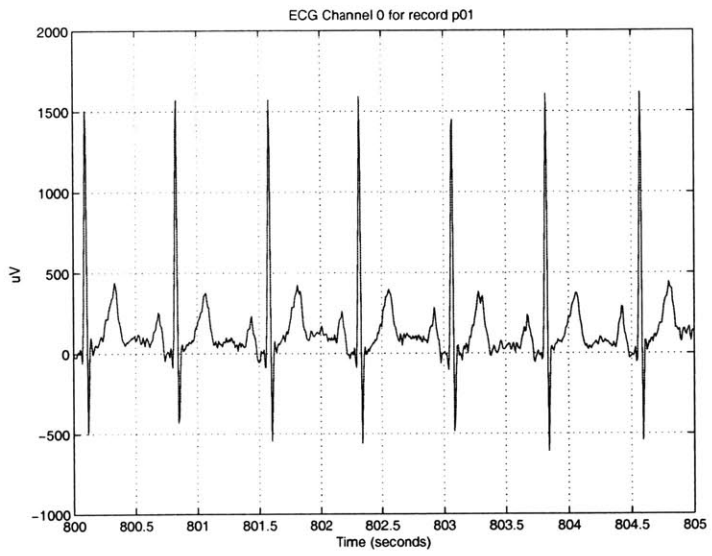

Figure 3-10: Segment of ECG from Figure 3-9 after low-pass filtering

All the ECG points between two baseline midpoints are then shifted appropriately using linear interpolation between the baseline midpoints. In Figure 3-11, the red line shows how much each point of the ECG is shifted so that the midpoints of every beat's baseline is moved to zero and the baseline corrected ECG signal in blue is produced.

An important question is: how are the baseline points determined for each beat? Section 3.3.1 describes how the start of the QRS complex was identified for each beat. A time window of 40 ms before the QRS complex was used to denote the PQ baseline.

It is important to eliminate low frequency noise from ECG prior to alternans analysis because it can smear any alternations present and prevent them from being detected.

Baseline correction method is preferred to high pass filtering because the low frequency noise can actually occur in a wide range of frequency bandwidth. As mentioned earlier the clinically relevant energy in an ECG is between 0.05 Hz and 50 Hz. If the low frequency noise is below 0.05 Hz, it can removed using a high pass filter without affecting the relevant ECG content. However, often the noise is of a higher frequency and high pass filtering with a high cut-off risks losing useful ECG

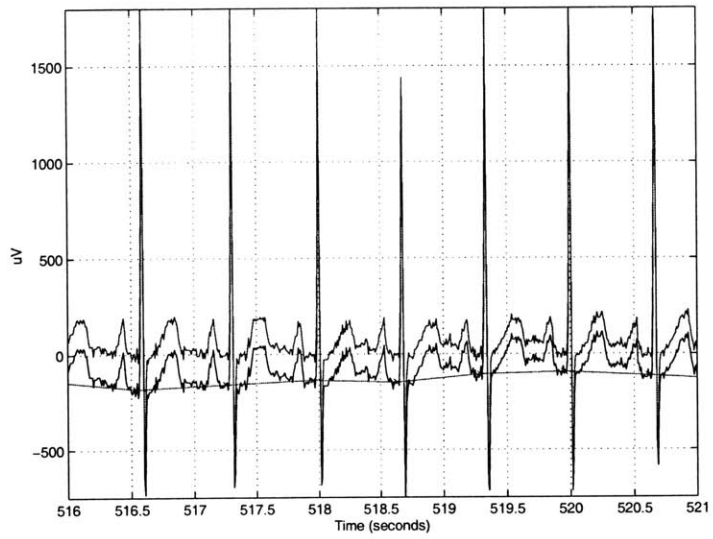

Figure 3-11: Demonstration of baseline alignment method. Black: old ECG. Red: line joining midpoints of baseline. Blue: new ECG

content.

Figure 3-12 shows a segment of ECG that has low frequency fluctuations which result in detected alternans. After baseline correction though, the ECG is aligned properly and no alternans is detected for this example (Figure 3-13).

3.2.3 High Pass Filtering for PQ baseline alternans measurement

For alternans analysis on the PQ baseline, high pass filtering is performed instead of baseline alignment to remove low frequency noise. The premise of baseline alignment is that the baseline of the ECG has to be at zero voltage for all beats. This rules out the possibility of alternans in the baseline and would eliminate any alternans that may have been present in the baseline. This is ok for the P-wave alternans measurement as we are focusing on the P-wave.

As mentioned earlier, high pass filtering has its drawbacks: the risk of losing significant energy content (or introducing/eliminating alternans) with a high cut-off versus not removing enough low frequency noise.

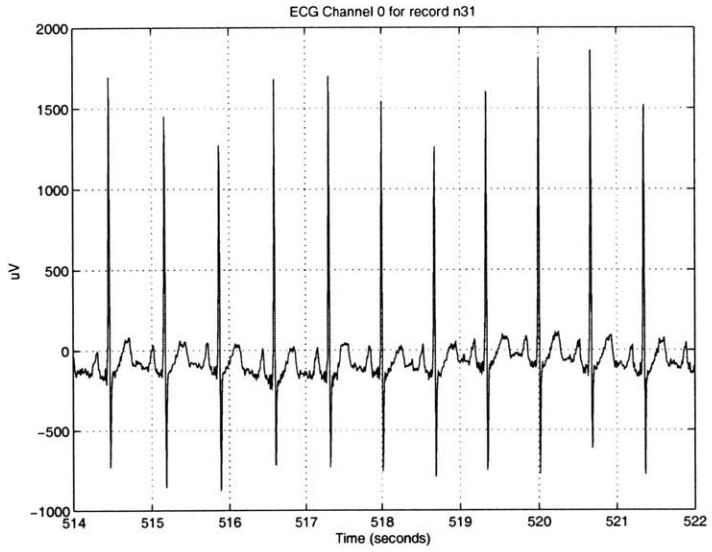

Figure 3-12: Segment of ECG that is not baseline aligned and produces false alternans

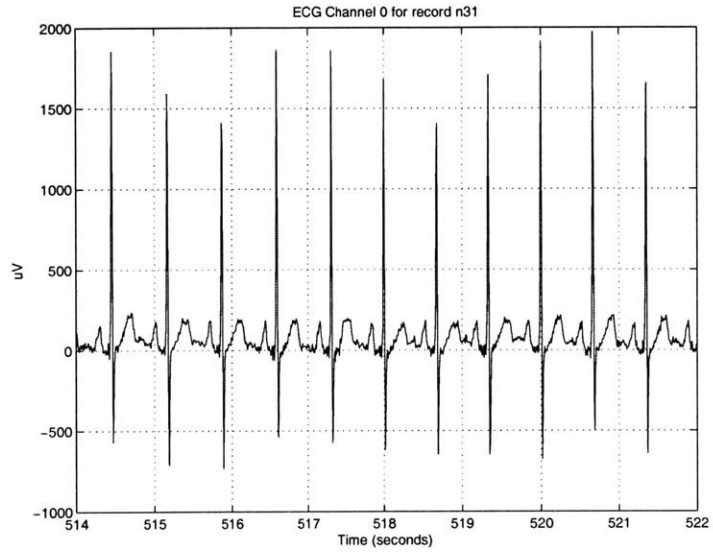

Figure 3-13: Segment of ECG from Figure 3-12 after baseline correction (no alternans detected)

We opted to use a high pass filter with a low cut-off to remove as much noise as possible and applied the algorithm assuming insignificance of noise beyond the cut-off for all ECG records under consideration. A 128-order digital FIR (finite impulse response) filter with a low frequency cut-off of 0.16 Hz was used. As with the low-pass filter, Matlab's (version 6.5) `fir1` command was used to implement the filter, with the following resulting characteristics: real impulse response with linear phase, normalized gain at cut-off frequency 0.16 Hz of -6 dB, and magnitude of 1 for the passband. The filter impulse response was windowed with a hamming window of length 129.

3.3 Baseline and P-wave Extraction

3.3.1 QRS Detection

An off-the-shelf QRS detector was used to identify the start of the QRS complex for each beat [28, 29]. This detector is accurate most of the time but not perfect, with a few missed beats and false beats in certain records. This is addressed in the next section (3.4) and section 4.1. In general, the performance of the QRS detector was considered to be robust enough for the purpose of the alternans algorithm.

3.3.2 Extraction of segments for alternans measurement

For the PQ baseline alternans measurement, a window of 40 ms before the identified Q point was used. This was 5 consecutive samples before the Q point for the ECG records we had (with sampling rate 128 Hz).

For the P-wave segment extraction, a variable number of samples is used. This is because the heart rate is variable across and within records. For every 128 beat segment on which the alternans algorithm was run, the average QQ interval length was computed. The arbitrary P-wave length for extraction was chosen to be 25% of the average QQ length. This percentage was derived from experimentation with different records and heart rates, and it was considered long enough to include the

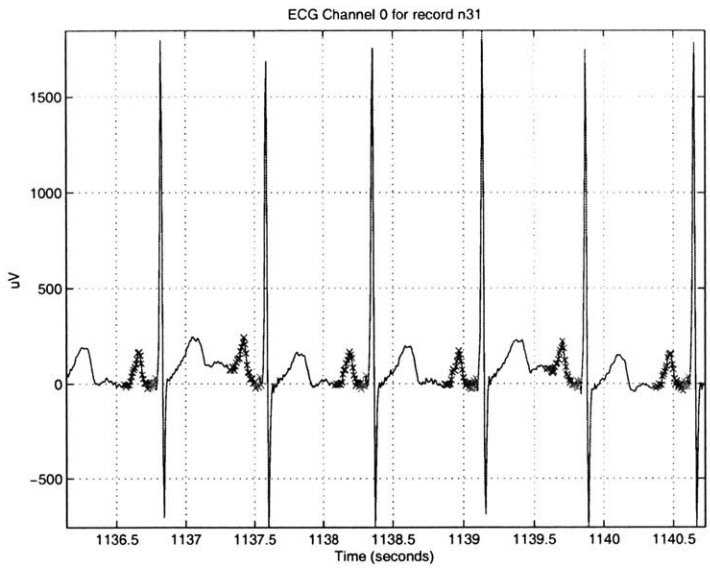

Figure 3-14: Segment of ECG showing extracted baseline and P-wave for each beat. Green = baseline. Red = P-wave.

whole P-wave for every record and short enough to exclude any part of the preceding T-wave.

Figure 3-14 shows the extraction of baseline and P-wave for a few beats of ECG.

The P-wave was extracted in this way (of using a QRS detector and selecting a few points prior) instead of using an automatic P-wave delineator because P-wave delineation is more difficult to implement than QRS-complex detection, for which many efficient automated algorithms exist. This is due to the low P-wave signal-to-noise ratio and the P-wave shape, which varies from one patient to another and sometimes even for a single patient. Also, for the alternans algorithm, an accurate P-wave is not required. Some part of the baseline on either side of the P-wave (TP and PQ segments) is acceptable because it would not contribute much to the alternans calculation.

3.4 Noise Correction

Since the ECG data we have is from Holter device, the extracted P-waves are often corrupted with noise. Section 3.2 earlier described how we removed periodic low and high frequency noise using filtering, and how (regular or irregular) shifts in the baseline (due to subject movement or breathing for example) were corrected. This section presents an attempt to remove or discount other kinds of irregular noise in which, for example, the baseline might be correct but the P-wave might be unexpectedly high, or a falsely detected beat might cause spurious P-wave values to be extracted.

3.4.1 Removal of outliers

Once the appropriate segments (P-wave or baseline) are extracted for alternans analysis, a matrix is constructed as described in section 3.1. Each row is a 128 length vector of values of a particular point in the chosen segment over 128 consecutive beats. The distribution of these values for a contiguous 128 beat region of ECG is considered to be a normal distribution. Any value $\pm$ 2 standard deviations from the median is removed and replaced with the median.

The standard deviation of this distribution is estimated by sorting the vector and using the 33.3%-th and 66.7%-th values. In a gaussian distribution, the third of the values in the middle lie in a confidence interval of $[-0.4309\sigma, 0.4309\sigma]$ (Figure 3-15). Hence the following equation can be used to estimate the standard deviation σ:

$$x_{\frac{2}{3}} - x_{\frac{1}{3}} = 2 * 0.4309 * \sigma$$

or

$$\sigma = \frac{x_{\frac{2}{3}} - x_{\frac{1}{3}}}{2*0.4309}$$

This is done for all the rows of the matrix, ie for all the points within the chosen segment any spurious values with respect to those points over time are removed. Replacing spurious values with the median minimizes the effect on the alternans algorithm. Figures 3-16 and 3-17 show an example of this.

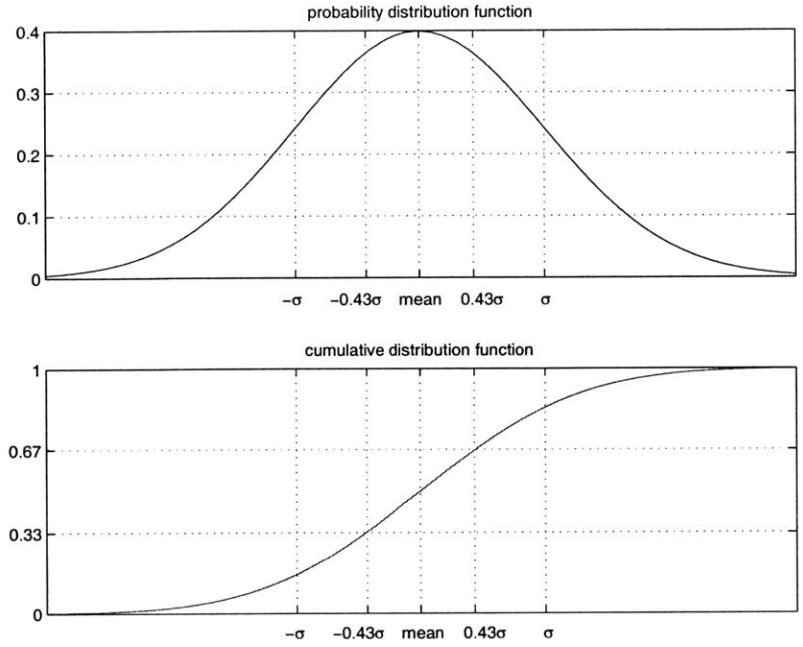

Figure 3-15: Normal distribution with some confidence intervals

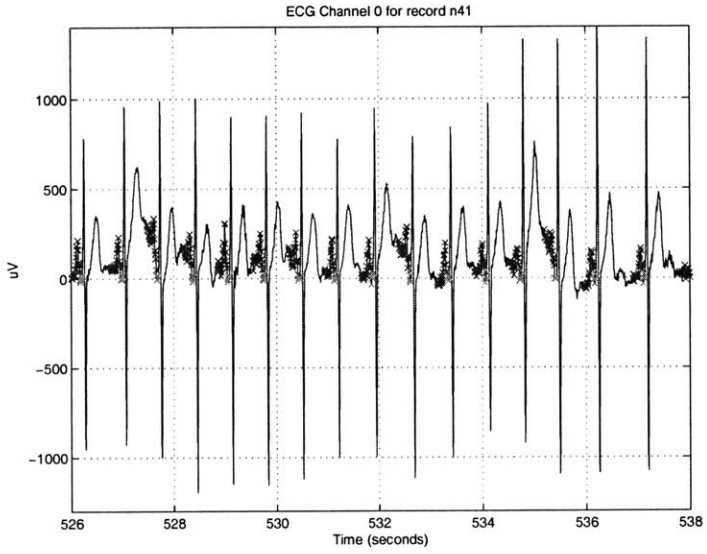

Figure 3-16: Segment of ECG before outlier removal (Figure 3-17)

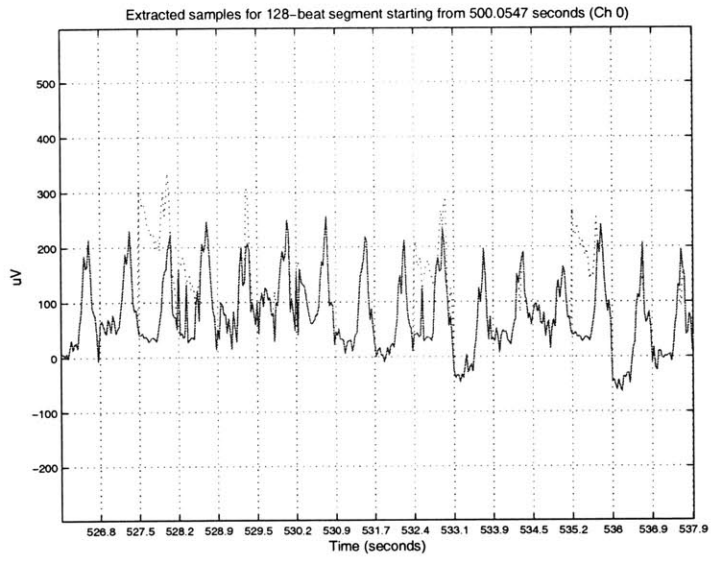

Figure 3-17: Segment of ECG after outlier removal. Refer to Figure 3-16. Blue dotted = Old P-waves. Red = New P-waves.

3.4.2 Detection and Replacement of bad beats

Sometimes an ECG recording is mostly clean but there are small bursts of noise or badly detected beats or spurts of atrial bigeminy or (atrial or ventricular) premature complexes. Often this can cause false alternans to be detected. Some of it is taken care of by the outlier removal method discussed above. Another technique we used was to monitor the QQ interval length. If the QQ interval length decreased by a 'significant' amount, the resulting beat usually gives rise to a 'bad' segment. Figure 3-18 shows a segment of ECG with an ectopic beat with shorter duration in which there is no P-wave and a part of the T-wave is selected as the P-wave. Our algorithm monitored the QQ interval length and whenever the next interval's length was at least 15% less than the previous interval, the whole segment extracted from the resulting beat was replaced with the median of the segments from all 128 beats. The replacement of the 'bad' segment in Figure 3-18 is shown in Figure 3-19. When more than 20% of beats in a 128 beat segment were 'bad', that segment was excluded from the alternans analysis. This is usually indicative of high noise or significant number of badly detected beats or long runs of atrial bigeminy or frequently occuring ectopic beats, and these cases

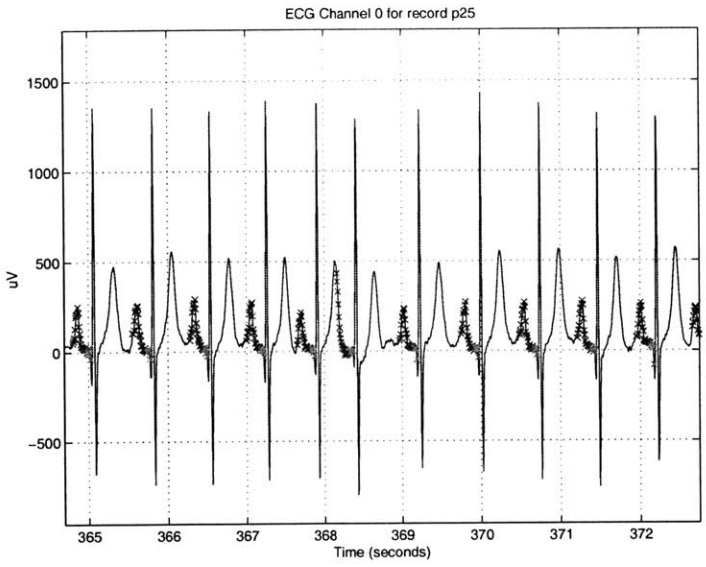

Figure 3-18: Segment of ECG showing part of a T-wave detected as P-wave

have to be excluded from the alternans analysis.

3.5 Alternans data over time

The ECG data we have available consists of 30 minute 2 channel recordings for each person. The algorithm is applied by having a 128 beat segment window of ECG that moves from the start of the ECG (of one channel) to the end in 16 beat shifts. The values in equations 3.1 are computed for each 128 beat window and a graph of alternans and noise voltage versus time is produced for the 30 minute signal. Regions of significant alternans ($AR > 3$) are shaded in the graph. A sample alternans voltage graph is shown in Figure 3-20.

A summary of the steps involved in computing alternans data for a channel of ECG is shown in the flowchart in Figure 3-21.

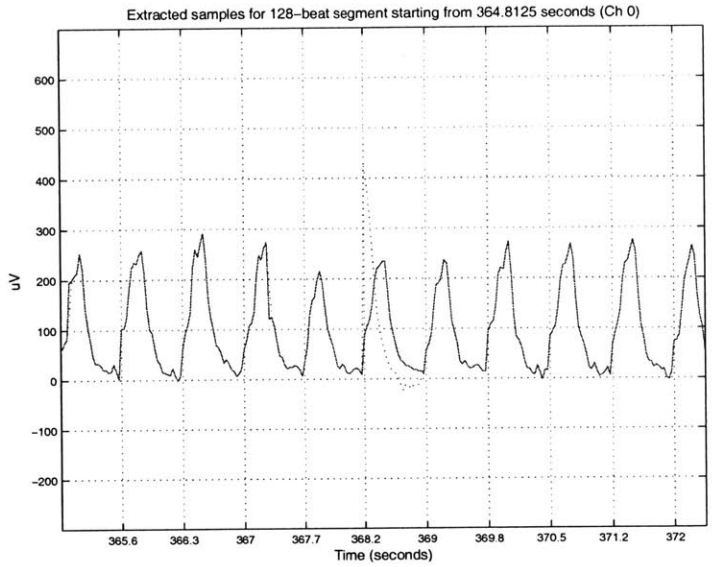

Figure 3-19: Corrected P-wave for bad beat in Figure 3-18. Blue dotted = Old P-waves. Red = New P-waves.

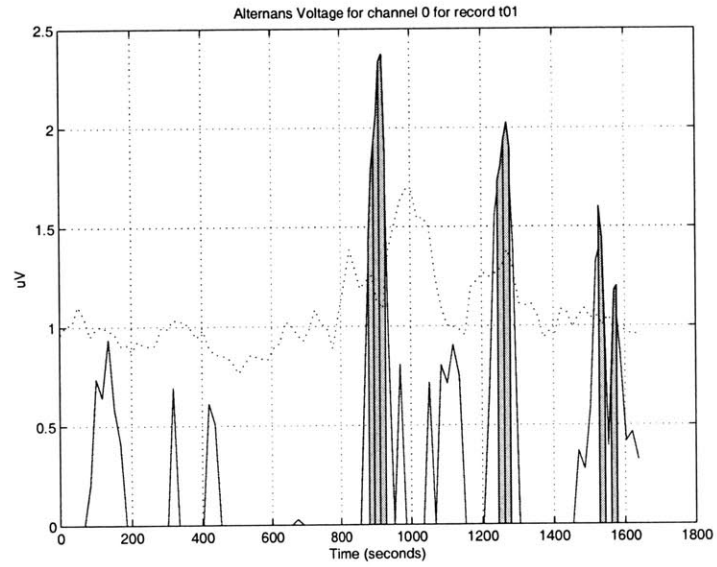

Figure 3-20: Sample Alternans Voltage graph. Dotted = Noise voltage. Shaded = Alternans is significant.

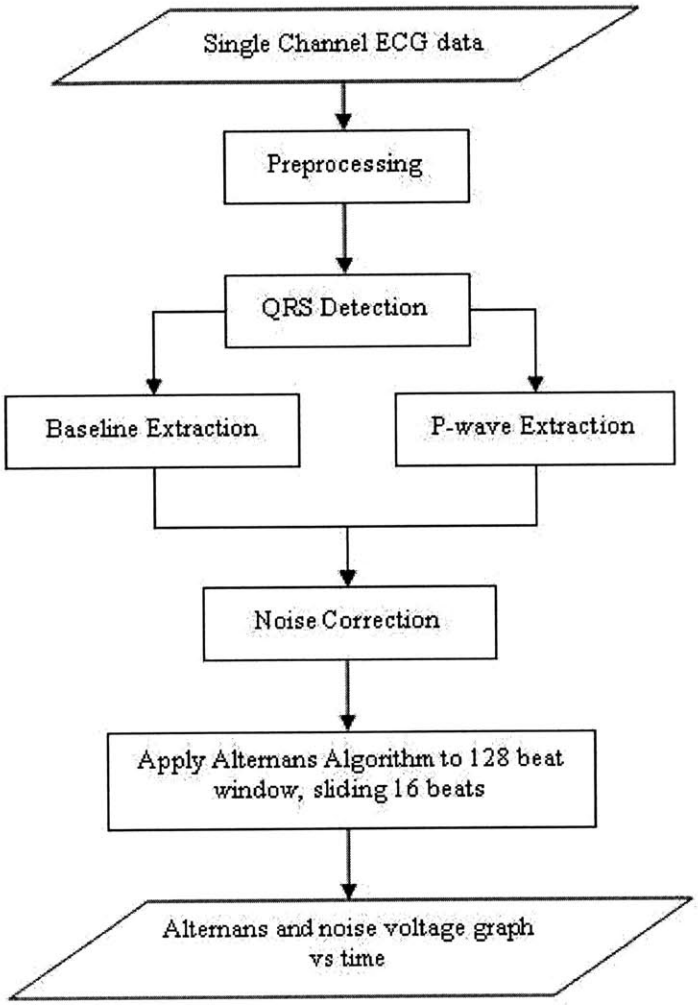

Figure 3-21: Flowchart showing various steps involved in the alternans algorithm

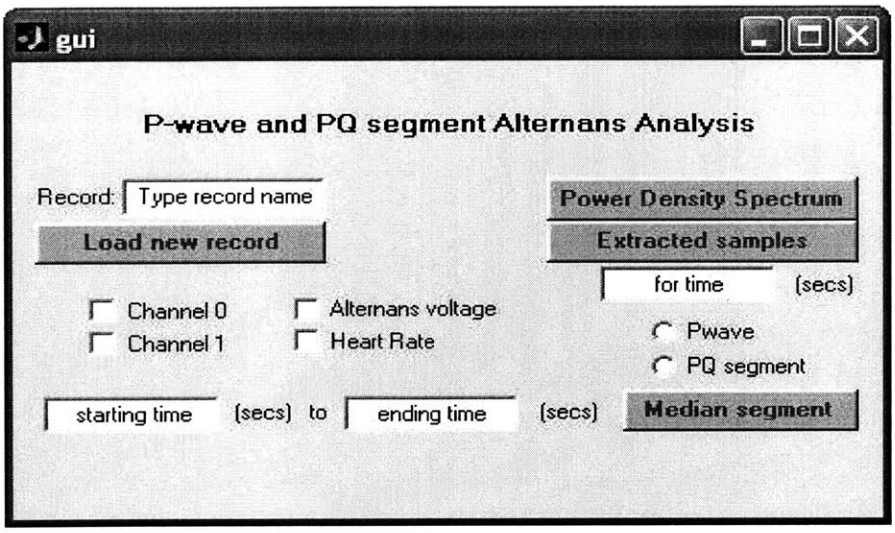

Figure 3-22: Screen shot of GUI

3.6 Implementation tool

A graphical tool was created to aid with the implementation of the algorithm. It was used to display ECG records, view the extraction of baseline and P-wave segments, and view the alternans graphs for each channel. The different options available in the graphical user interface (GUI) can be seen in the screen shot in Figure 3-22. The GUI was very helpful in the analysis, debugging, fine-tuning, refinement and testing of the alternans algorithm.

Chapter 4

Analysis

In this chapter, we present the analysis techniques used to explore the existence of predictive characteristics in the ECG alternans data generated using the system implementation described in the previous chapter. The results of the analysis allow us to make conclusions about the predictive ability of alternans for Paroxysmal Atrial Fibrillation.

4.1 ECG Database Available

We acquired the ECG database for applying and testing the alternans algorithm described in the previous chapter from an online resource for physiologic signals called PhysioNet [27].

4.1.1 Description of the Database

The database consisted of 100 records. Each record had a pair of 2 channel ECG signals. 47 out of 100 records were from 'normal' people (ie those with no documented case of Paroxysmal Atrial Fibrillation (PAF)) and 53 were from people with PAF. In the 'normal' records, the two ECG signals in the pair were 30 minute recordings from different points in time. In the 'abnormal' records, one ECG signal in the pair was a 30 minute recording distant from any episode of PAF (defined as at least 45 minutes

before or after an episode of PAF). The other 30 minute recording was just before an episode of PAF.

4.1.2 Formulation of Tasks

The following questions have to be considered when investigating the possibility of P-wave and/or PQ segment alternans as a marker and predictor of Paroxysmal Atrial Fibrillation:

Is there a (significant) difference (in alternans levels) between normal and abnormal records? The answer to this question would indicate whether it is possible to distinguish people with and without PAF using alternans testing.

Is there a difference between normal records and abnormal records distant from PAF? A positive answer would mean that detection of PAF in abnormal records is possible even if an episode of PAF is not imminent.

Is there a difference between abnormal records distant from PAF and abnormal records just before PAF? Increased levels of alternans just before an episode of PAF would show that the imminence of PAF can be predicted using alternans monitoring. Even if alternans levels are specific to individual people, a sharp relative increase could be an indicator for imminent PAF episode.

Finally, *is there a difference between normal records and abnormal records just before PAF?* If the incidence of PAF in a person cannot be detected from an ECG record when an episode is far away, perhaps it can be detected when an episode is imminent, which might not be too useful, but regardless would be an important discovery.

These questions were answered using the learning techniques described in section 4.3 and applying them to the alternans versus time data generated for each record

(as described in the previous chapter).

4.1.3 Exclusion of bad records

In order to make a conclusive study, any records that cannot be used conclusively have to be excluded from the analysis. This includes certain records which are very noisy (even after the noise correction methods mentioned in the previous chapter were applied), or those on which the QRS detector did not work well resulting in an excessive number of false or missed beats.

16 out of 100 records were excluded from the study in two steps. First, an automated script was written that looked at the QQ intervals produced for each ECG record (using the QRS detector mentioned in 3.3.1). Any beats that had a QQ interval at least 40% less than the previous interval were marked as 'bad' beats. Any record which had more than 10% of these 'bad' beats were marked and then observed visually. Most of the time these were false beats and sometimes this occurred due to frequent runs of atrial bigeminy [1] where the QQ interval fluctuated considerably. The bigeminy records were kept as they were not affected by the alternans algorithm.

Once the records with considerable number of false and missed beats were eliminated, the rest of the records were observed visually one by one to see if they were suitable to be used for the alternans analysis. Any records with a lot of noise and with bad P-waves as a result or too many missed beats (Figures 4-1 and 4-2) were eliminated.

Eventually 84 out of 100 records were used. Of these, 37 were normal and 47 were abnormal. Often one of the pair was 'bad' in a record, but the whole record was eliminated for ease and uniformity of analysis.

When the alternans algorithm was run, 4 records were classified as indeterminate as they had bigeminy for the whole 30 minute duration, and so there were no 128 beat segments that could be used for alternans measurement. Therefore, essentially

[1] Atrial Bigeminy is an arrhythmia where every other beat is a premature atrial complex (PAC). It indicates neither the presence nor absence of PAF. Moreover, P-wave alternans analysis is not applicable as every other beat usually does not have a P-wave. The alternans algorithm takes care of this as described in section 3.4.2

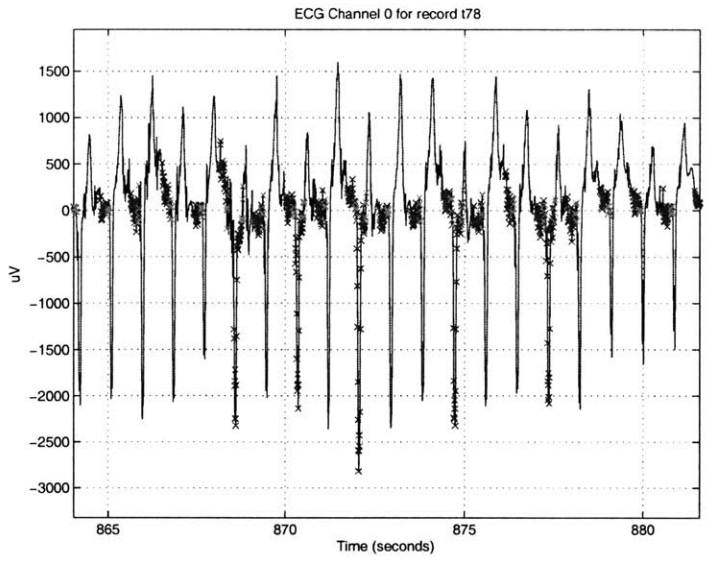

Figure 4-1: An ECG record with noise and false beats resulting in bad P-waves (red)

there were 80 records that were used eventually, of which 35 were normal and 45 were abnormal.

4.2 Alternans measures

The alternans algorithm described in the previous chapter was run on all the records to produce a graph of alternans voltage vs time as shown in Figure 3-20, with the regions of significant alternans ($AR > 3$ as defined in equation 3.1) shaded.

A few measures were extracted from these graphs for each record for application of learning models described in section 4.3. The factors which are important in considering alternans as a predictor are: the magnitude of the alternans voltage, duration of significant alternans regions, and frequency of significant alternans. Hence the following values were extracted from the alternans data and fed to the learning algorithm:

- **Percentage of significant alternans segments above a particular threshold voltage:** Three threshold voltages were used: 0 uV, 2 uV, and 4 uV. The

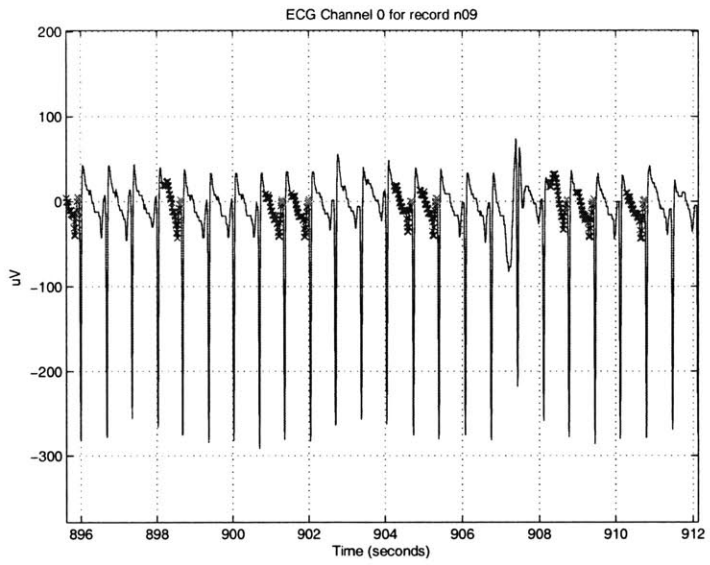

Figure 4-2: An ECG record with too many missed beats, resulting in longer QQ interval and hence longer segment chosen for P-waves (red)

percentage of all 128-beat segments in the 30 minute ECG record with significant alternans [2] voltage greater than each of the threshold voltages was calculated.

- **Average duration of significant alternans regions** This marker determines the consistency or lastingness of alternans. The duration is measured in number of consecutive 128-beat segments separated by 16 beats that have significant alternans. The average for the whole 30 minute ECG record was calculated.

- **Average Alternans Index** The alternans ratio (AR) was defined in 3.1 as a measure of the significance of the alternans voltage with respect to noise. Alternans was considered significant if AR was greater than 3. The value of AR for a particular alternans region could also be a marker for PAF besides the alternans voltage. The voltage may be very high but if the noise is also high, the AR is low. For every segment with significant alternans, the AR minus 3 (so that insignificant alternans is index of zero) was used as another variable for the learning model, and this was called the alternans index. The average

[2]Defined as *Alternans ratio* $>$ 3 in equation 3.1

Table 4.1: Example of computed alternans measures

% of SA segments above threshold voltage:			Average Alternans	Areas of contiguous SA segments	
0 uV	2 uV	4 uV	Index	Max	Average
3.03	0.00	0.00	1.10	1.19	0.57

Average duration of SA segments	Average alternans voltage in SA regions (uV)	Average alternans voltage over 30 min ECG record (uV)
1.67	0.34	0.01

SA = significant alternans

alternans index for the ECG record was calculated.

- **Areas of contiguous segments with significant alternans:** This is basically the sum of the alternans voltages in each consecutive 128 beat segment with significant alternans. The maximum and mean areas for each record were used.

- **Average voltage of significant alternans regions:** This determines how strong the alternans is on average in all the significant alternans regions of a record.

- **Average alternans voltage over all segments (30 min ECG record):** This value is a different marker than the previous one as it includes regions without significant alternans where the voltage is taken to be zero. Thus this is a measure of the average alternation in the whole 30 minute record.

Table 4.1 shows an example of the data above computed from the alternans graph shown in Figure 4-3.

4.3 Learning techniques

4.3.1 Definition of Classification problem

The measures derived from the ECG alternans data in the previous section are considered sufficient to include all aspects of alternans behavior in the ECG waveform.

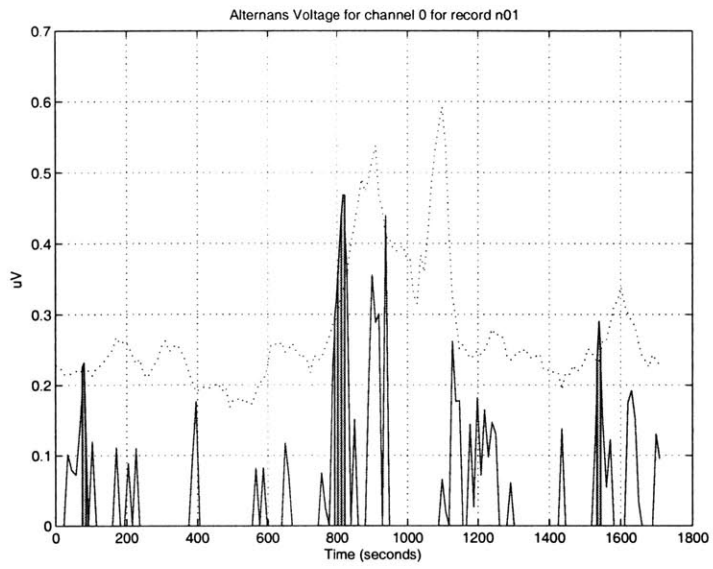

Figure 4-3: Alternans graph from which measures in Table 4.1 were calculated

There are a total of 36 variables produced in this way (9 for each channel, therefore 18 each for P-wave and PQ segment alternans for both channels).

The tasks defined in section 4.1.2 lead to a four-part classification problem. There are four pairs of data sets on which classification needs to be performed. We use the following labels to denote each data set:

normal ECG records from subjects with no documented case of PAF.

70 records (from 35 subjects).

abnormal ECG records from subjects with PAF.

90 records (from 45 subjects).

distant Abnormal records that are distant (> 45 min) from a PAF episode.

45 records.

imminent Abnormal records that are just prior to an episode of PAF.

45 records.

Classification is performed on the following four pairs of data sets:

Table 4.2: Derivation and validation sets used for the different classification set pairs

	classification pair	set type	total	PAF	normal
1	normal vs abnormal	derivation	**100**	56	44
		validation	**60**	*34*	*26*
2	normal vs distant	derivation	**50**	28	22
		validation	**30**	*17*	*13*
3	distant vs imminent	derivation	**56**	28	28
		validation	**34**	*17*	*17*
4	normal vs imminent	derivation	**50**	28	22
		validation	**30**	*17*	*13*

1. `normal` vs `abnormal`
2. `normal` vs `distant`
3. `distant` vs `imminent`
4. `normal` vs `imminent`

For normal vs distant and normal vs imminent classifications, a random record out of the pair for each patient is selected for the normal records to make the data set pairs evenly sized.

4.3.2 Creation of Validation Sets and Derivation Sets

Of the 80 records, 30 were selected randomly for use in validation or test sets. The remaining 50 records were used for developing the predictive models that were then evaluated on the test sets.

Hence, for each of the four pairs of classification sets described above, the number of samples used in the derivation and test sets are shown in Table 4.2.

4.3.3 Randomization and Cross-validation

The derivation set was divided into 3 equal sized subsets randomly. Each subset was in turn used as the 'holdout' set. The model was trained on the remaining 2 subsets and evaluated on the 'holdout' set. This technique is called cross-validation. This

process of random splitting into 3 subsets was repeated 10 times to give 30 pairs of learning and holdout sets that were used for the model building.

Cross-validation is a useful technique when the number of samples is small compared to the number of variables (as is the case in our problem). Randomization coupled with cross-validation gives a distribution of learning and holdout set performance indexes that gives an idea of the effect of data splitting on model performance. For example, a high variance indicates high dependence of performance on the choice of subsets used for training and testing.

For each classification problem, model building was done separately using logistic regression and neural networks on the derivation sets. The performance of the best models produced using logistic regression and neural networks were then compared on the validation data.

4.3.4 Logistic Regression

Binary logistic regression is a variation of linear regression in which the observed outcome is one of two values, which usually represents the occurrence or non-occurrence of some outcome event. Hence it is useful for classification problems where an observation has to be predicted as being one of two possible events.

In linear regression, the dependent variable is a linear combination of one or more independent variables. Methods such as least squares error are used to find the coefficients or weights of these independent variables and the intercept (or constant term) that produce the best linear relationship between the inputs and the output.

In logistic regression, a non-linear sigmoid function is applied to the linear combination of the inputs to transform the range of the output from minus infinity and plus infinity to 0 and 1. This produces a formula that predicts the probability of the occurrence of an event as a function of the independent variables.[3]. For classification

[3]The logistic regression function gives a probability between 0 and 1 of the input matrix X corresponding to one of the two binary outcomes. For a particular sample i, $p_i = \frac{1}{1+e^{-\beta_0+\beta_i X_i}}$ where β_0 is a constant intercept and β_is are the coefficients or weights for the input variables

problems, a threshold probability (e.g. 0.5) is used, above and below which the binary outcome is specified.

The coefficients of the input variables (and the constant term) are computed using maximum likelihood estimation (MLE). MLE is an iterative algorithm that selects the coefficients that maximize the probability of observing the sample outcomes from the associated inputs.

We used built-in Matlab (version 6.5) program called glmfit to implement the logistic regression models.

Variable Selection

We were interested in measuring the adequacy of a few parameters in classifying accurately the four data set pairs above. The parameters of interest are: alternans measurement category (eg. percentage of alternans segments above a certain threshold voltage), P-wave or PQ segment alternans, ECG channel (0 or 1), and various combinations of each.

Logistic regression models were built for a variety of combinations of parameters and variables. In addition, the techniques of forward variable selection and most popular variables selection were used to automatically select the 10 'best' variables from the large pool of 36 variables.

Variable selection is necessary because the number of variables is very large for the small number of samples in our data sets (100 in the case of the first data set pair above). This causes *overfitting*[4] in the training set and poor performance on the test set.

Variable Categories The following variable categories were used in turn for training the model and evaluating the resulting predictive performance of each:

1. P-wave channel 0 All variables (9)

2. P-wave channel 1 All variables (9)

[4]Overfitting is the problem of memorizing the data set instead of identifying the underlying distribution. Restricting model complexity is a way of avoiding overfitting.

3. PQ segment channel 0 All variables (9)

4. PQ segment channel 1 All variables (9)

5. Percentage of alternans segments above particular voltage All variables [5] (3*4=12)

6. Average duration of alternans segments ALL (1*4=4)

7. Average alternans index ALL (1*4=4)

8. Areas of significant alternans segments ALL (2*4=8)

9. Alternans averages ALL (2*4=8)

Forward Variable Selection This is an iterative algorithm in which one variable is selected at a time and added to the list of variables selected. First, learning is performed using only one variable from each of the 36 variables in turn. The 'best' variable out of the 36 i.e. the one producing the best learning set classification performance is selected. Each of the remaining variables is in turn added to this variable to see which one improves the performance the most. In this way, variables are added and the process is stopped when there is no significant improvement in the learning set classification performance and/or the number of variables has increased significantly.

This process was performed for each of the 30 randomization splits (discussed in section 4.3.3), producing a distribution of performance indexes for forward variable selection.

Most Popular Variables Selection Forward variable selection produces 30 lists of 10 selected variables. Due to the different subsets used for learning and holdout for each of the 30 cases, different sets of variables are selected each time. From the 30 sets of 10 variables, the 10 most popular variables are picked for producing another model for the derivation set.

[5] both channel 0 and 1 and P-wave and PQ segment alternans

Summary for Logistic Regression

A total of 330 models were produced using logistic regression. This includes 9*30 models for the arbitrary variable categories (9 categories and 30 random splits), 30 models for forward selection, and 30 models for most popular variables. The best model category (e.g. most popular variables) was selected on the basis of average performance on the holdout sets for the different variable selection techniques. Of the 30 models in this category (30 splits), the one with the best performance on the holdout set was chosen as the final model to be tested on the validation set.

The holdout set contains data that was not seen by the training algorithm and hence performance on this set is important. The final model produced has to perform well on data not involved in learning such as the validation set.

4.3.5 Neural Network

Neural networks are a more general form of logistic regression. There can be multiple layers and hidden units in each layer that combine to form a nonlinear function of the inputs. In this way neural networks are more flexible than logistic regression and can model a more complex relationship between the inputs and outputs. Like logistic regression, the parameters of a neural network are also determined using maximum likelihood estimation, which chooses the parameters that maximize the probability of observing the sample outcomes given the inputs. A variety of numerical optimization algorithms, from simple gradient descent to more complicated second-order methods, can be used to determine the optimal parameter values.

To implement the neural network models, we used Netlab's neural network toolbox for Matlab [30]. A two-layer network with 4 hidden units were used. The network optimization was performed using scaled conjugate gradients. We used all 36 variables as inputs.

To determine the effect of initial conditions on the final model, we chose 10 random initialization seeds (these can be given as inputs for the initial network) and used them on each of the 30 training/holdout data splits that were used to build the logistic

regression models, resulting in 300 models. The best model was chosen to be the one with the best performance on the holdout set.

The following section describes measures that were used to characterize and evaluate the performance of a model in order to select the best model.

4.3.6 Performance measures and Testing

The C-index was the main performance measure that was used to describe the performance of a particular model. The C-index is equivalent to the area under the ROC curve[6]. During forward variable selection, the C-index of the learning subset was used to iteratively select the single best variable to add to the list of already chosen variables.

Once model building had been performed, the distribution of the holdout set C-indexes over the 30 randomization splits for each of the models was used to select the best model. This includes the model with the highest mean holdout set C-index and minimum standard deviation.

The best performing logistic regression and neural network models were then tested on the validation sets. The C-index of the model applied to the validation set gives the overall performance of the model on the validation set.

The ROC curve shows the tradeoff between the sensitivity and specificity for the model performance. Also, the maximum relative risk ratio was determined for the particular model. Relative risk (RR) is a ratio of likelihood of disease given a person is tested positive to the likelihood of disease given the person is tested negative. The higher the ratio, the greater the value of the discriminating test. RR is defined as:

[6]The Receiver Operating Characteristic (ROC) curve is a commonly used tool for evaluating the performance of diagnostic tests or prediction models. The ROC curve is a plot of sensitivity vs. (1-specificity) over a range of threshold values. The area under the ROC curve is a standard measure of discrimination, which is one measure of the accuracy of a model. The greater the area under the ROC curve, the greater the ability of the test to discriminate between normal and abnormal values. The area under an ROC curve can range from 0.5 (no discriminating ability) to 1.0 (perfect discrimination of normal and abnormal cases).

$$RR = \frac{PPV}{1-NPV}$$

$$where$$

$$PPV\ (Positive\ Predictive\ value) = \frac{\#\ of\ true\ positives}{(\#\ true\ positives + false\ positives)} \tag{4.1}$$

$$and$$

$$NPV\ (Negative\ Predictive\ value) = \frac{\#\ of\ true\ negatives}{(\#\ true\ negatives + false\ negatives)}$$

Chapter 5

Results

5.1 Statistics of data

After deriving P-wave and PQ segment alternans information from all the ECG records available in the database, summary statistics such as mean, median, etc. were computed for the ECG categories of normal, abnormal, distant PAF and imminent PAF. These statistics are shown in appendix A. The complete alternans data for all the records is reproduced in appendix B.

A series of **t-tests** were carried out to determine if there were significant statistical differences in the means of individual variables between the four pairs of data sets[1]. In particular, the tests were carried out to see if the mean for a variable in one data set was significantly greater than the mean for the same variable in the other data set.

Table A.5 in appendix A shows the results for individual variables and Table 5.1 shows the summary for all variables for a particular set-pair comparison. The proportion of all the 36 variables in which the mean for one data set is significantly greater than the mean for the other data set is shown. For example using a confidence level of $p = 0.1$, for 12 of the 36 variables, the means are greater in the distant PAF set compared to the normal set, and only for 2 variables, the means in the normal set are higher. More notable is the statistic for imminent vs normal, where 17 variables

[1]section 4.3.1

Table 5.1: T-test comparisons showing proportion of variables significantly greater in mean for one set versus another

	$p < 0.05$		$p < 0.1$	
	count (/36)	%	count (/36)	%
Abnormal > Normal	11.00	31%	15.00	42%
Distant > Normal	7.00	19%	12.00	33%
Imminent > Distant	5.00	14%	10.00	28%
Imminent > Normal	13.00	36%	17.00	47%
Normal > Abnormal	0.00	0%	2.00	6%
Normal > Distant	1.00	3%	2.00	6%
Distant > Imminent	0.00	0%	1.00	3%
Normal > Imminent	0.00	0%	0.00	0%

have higher means in the imminent PAF set and no variable in the normal set which has a higher mean than the imminent set.

Similarly, observing the medians of the variables for the different data sets shows the imminent PAF sets have predominantly higher medians for most of the variables than both normal and distant sets (72% and 64% of all variables respectively). However, the medians for normal and distant PAF sets are not distinctly different and perhaps this may mean that a discrimination between PAF and normal patients is not possible when an episode of PAF is not imminent. Even though the medians are not significantly higher in the distant PAF vs normal sets, the means are, for some of the variables as shown by the t-test. This may mean that it might be possible to identify some of the distant PAF records, if not most, due to their high alternans values.

5.2 Learning results

5.2.1 Logistic Regression

Performance for Variable Categories

Table 5.2 shows the holdout set performance of the different variable categories when used in the logistic regression model building. The 'averages' variable category performs the best for all four classifications. Thus, the average significant alternans

voltage is a reasonably good marker for PAF.

Best learning models

Table 5.3 provides a summary of the best logistic regression models developed for each classification. The best average holdout set C-indexes are between 0.66–0.70 for the four classifications, which is a good discrimination for a small holdout set.

The final logistic regression model chosen for each classification is shown highlighted in Table 5.3.

An example of the best logistic regression model selected is shown in Table 5.4 for 'normal vs abnormal'. This is the "10 most popular variables" model. The variables selected are shown along with their β coefficients. Some of the variables have negative β coefficients but their values are small and so their effect is lower than the other variables.

5.2.2 Neural Network

Table 5.5 shows the summary for the 300 models developed for each classification using neural networks. For each of the 10 random seeds used, the average holdout set C-index is shown for the same 30 randomization splits. The learning performance for neural networks is not as good as logistic regression. This is likely because of the small data sets used and the possibility of overfitting in the neural network model. The complexity of neural networks provides a flexible and powerful model building technique; however, with a small data set, the abstraction of the underlying relationship between the relatively greater number of independent variables is more difficult than a simpler model building technique such as logistic regression. The best holdout set C-indexes for the neural network models were between 0.61–0.65.

The final neural network model chosen for each classification is highlighted in table 5.5.

Table 5.2: Logistic regression learning results using different variable categories

normal vs abnormal

	Training set		Holdout set	
Variable Category	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index
P-wave ch 0 ALL	0.70	0.03	0.55	0.04
P-wave ch 1 ALL	0.73	0.04	0.56	0.05
PQ ch 0 ALL	0.72	0.04	0.56	0.04
PQ ch 1 ALL	0.70	0.04	0.55	0.04
Voltage ALL	0.78	0.03	0.57	0.06
Duration ALL	0.66	0.05	0.59	0.06
Alt Ratio ALL	0.71	0.05	0.61	0.07
Areas ALL	0.71	0.04	0.57	0.06
Averages ALL	**0.80**	**0.03**	**0.65**	**0.06**

normal vs distant

	Training set		Holdout set	
Variable Category	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index
P-wave ch 0 ALL	0.82	0.06	0.60	0.09
P-wave ch 1 ALL	0.81	0.06	0.60	0.07
PQ ch 0 ALL	0.85	0.05	0.62	0.07
PQ ch 1 ALL	0.84	0.06	0.61	0.08
Voltage ALL	0.90	0.05	0.63	0.08
Duration ALL	0.65	0.05	0.62	0.08
Alt Ratio ALL	0.73	0.06	0.65	0.10
Areas ALL	0.80	0.06	0.63	0.10
Averages ALL	**0.86**	**0.05**	**0.66**	**0.10**

distant vs imminent

	Training set		Holdout set	
Variable Category	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index
P-wave ch 0 ALL	0.84	0.06	0.60	0.08
P-wave ch 1 ALL	0.83	0.05	0.61	0.09
PQ ch 0 ALL	0.82	0.06	0.62	0.07
PQ ch 1 ALL	0.77	0.07	0.62	0.09
Voltage ALL	0.89	0.05	0.62	0.07
Duration ALL	0.71	0.05	0.62	0.07
Alt Ratio ALL	0.74	0.07	0.63	0.09
Areas ALL	0.76	0.06	0.61	0.08
Averages ALL	**0.85**	**0.06**	**0.65**	**0.11**

normal vs imminent

	Training set		Holdout set	
Variable Category	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index
P-wave ch 0 ALL	0.83	0.06	0.60	0.10
P-wave ch 1 ALL	0.81	0.05	0.62	0.08
PQ ch 0 ALL	0.85	0.05	0.62	0.08
PQ ch 1 ALL	0.83	0.08	0.59	0.09
Voltage ALL	0.91	0.05	0.64	0.10
Duration ALL	0.76	0.06	0.66	0.10
Alt Ratio ALL	0.75	0.05	0.64	0.09
Areas ALL	0.78	0.06	0.61	0.06
Averages ALL	**0.87**	**0.05**	**0.67**	**0.10**

Best variable category highlighted

Table 5.3: Logistic regression learning results showing the average C-indexes from the 30 random splits of the derivation data set

normal vs abnormal

	Training set		Holdout set		
Model	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
All	0.75	0.04	0.59	0.06	0.73
Forward	0.88	0.04	0.63	0.08	0.80
Most popular	**0.83**	**0.04**	**0.68**	**0.08**	**0.86**
Best variable category	0.80	0.03	0.65	0.06	0.76

normal vs distant

	Training set		Holdout set		
Model	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
All	0.84	0.05	0.63	0.09	0.83
Forward	0.99	0.02	0.65	0.10	0.86
Most popular	**0.96**	**0.03**	**0.70**	**0.11**	**0.88**
Best variable category	0.86	0.05	0.66	0.10	0.89

distant vs imminent

	Training set		Holdout set		
Model	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
All	0.82	0.06	0.62	0.08	0.83
Forward	0.96	0.05	0.59	0.06	0.71
Most popular	**0.89**	**0.06**	**0.66**	**0.10**	**0.90**
Best variable category	0.85	0.06	0.65	0.11	0.94

normal vs imminent

	Training set		Holdout set		
Model	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
All	0.84	0.05	0.63	0.09	0.84
Forward	0.99	0.02	0.63	0.08	0.80
Most popular	0.91	0.05	0.65	0.10	0.86
Best variable category	**0.87**	**0.05**	**0.67**	**0.10**	**0.97**

Table 5.4: Beta coefficients from the best logistic regression model for 'normal vs abnormal'. This model was obtained using the split with best holdout set c-index from the 10 "most popular" selected variables

	Variable	Beta
	constant	-0.8698
P-wave ch 0	% of SA segments above 0 uV	-0.0831
	Avg SA voltage	0.1103
P-wave ch 1	% of SA segments above 4 uV	3.9867
	Area of contiguous segments (max)	-0.3269
	Avg duration of SA segments	6.312
PQ ch 0	% of SA segments above 0 uV	-0.0581
	% of SA segments above 4 uV	-0.1162
	Avg Alternans Index	0.3522
	Area of contiguous segments (avg)	-0.0025
PQ ch1	Avg Alternans Index	1.127

Table 5.5: Neural network learning results showing the average C-indexes from the 30 random splits of the derivation data set

normal vs abnormal

	Training set		Holdout set		
Seed	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
1	**0.85**	**0.03**	**0.66**	**0.09**	**0.83**
2	0.83	0.04	0.62	0.08	0.75
3	0.83	0.03	0.65	0.07	0.78
4	0.82	0.04	0.65	0.09	0.83
5	0.84	0.04	0.65	0.07	0.80
6	0.82	0.04	0.62	0.07	0.76
7	0.84	0.04	0.64	0.08	0.82
8	0.83	0.04	0.63	0.08	0.81
9	0.86	0.04	0.64	0.07	0.81
10	0.81	0.04	0.64	0.09	0.84
Average	0.83	0.04	0.64	0.08	0.80

normal vs distant

	Training set		Holdout set		
Seed	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
1	0.72	0.06	0.60	0.08	0.80
2	0.64	0.09	0.61	0.07	0.78
3	0.66	0.10	0.62	0.09	0.87
4	0.75	0.08	0.62	0.09	0.81
5	**0.78**	**0.05**	**0.63**	**0.08**	**0.84**
6	0.73	0.07	0.61	0.08	0.86
7	0.71	0.12	0.59	0.08	0.79
8	0.74	0.07	0.60	0.08	0.90
9	0.77	0.07	0.61	0.08	0.86
10	0.68	0.06	0.60	0.07	0.71
Average	0.72	0.08	0.61	0.08	0.82

distant vs imminent

	Training set		Holdout set		
Seed	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
1	0.68	0.05	0.59	0.08	0.84
2	0.71	0.09	0.60	0.07	0.73
3	0.76	0.07	0.59	0.06	0.72
4	0.66	0.08	0.61	0.07	0.78
5	0.72	0.07	0.60	0.08	0.75
6	0.66	0.07	0.59	0.06	0.71
7	**0.74**	**0.05**	**0.63**	**0.09**	**0.78**
8	0.71	0.05	0.62	0.09	0.80
9	0.68	0.05	0.62	0.09	0.80
10	0.71	0.05	0.60	0.09	0.88
Average	0.70	0.06	0.60	0.08	0.78

normal vs imminent

	Training set		Holdout set		
Seed	Mean C-index	Std Dev C-index	Mean C-index	Std Dev C-index	Best C-index
1	0.80	0.05	0.68	0.12	0.95
2	0.78	0.07	0.65	0.10	0.87
3	0.75	0.07	0.62	0.08	0.83
4	0.73	0.09	0.62	0.09	0.85
5	0.76	0.09	0.69	0.10	0.86
6	0.70	0.07	0.66	0.09	0.84
7	0.78	0.05	0.62	0.08	0.80
8	**0.76**	**0.05**	**0.70**	**0.10**	**0.86**
9	0.71	0.11	0.64	0.11	1.00
10	0.76	0.06	0.62	0.08	0.82
Average	0.75	0.07	0.65	0.09	0.87

5.3 Testing results

The best logistic regression and neural network models were applied to the validation sets to evaluate their performance. Table 5.6 shows the results for the four classifications using the best logistic regression and neural network models for each. Figures 5-1, 5-2, 5-3, and 5-4 show the Receiver Operating Characteristic (ROC) curves for the tests.

The maximum relative risk ratio (RR) is shown for each classification. RR is defined in equation 4.3.6. The maximum RR corresponds to a particular value on ROC curve, i.e. a particular threshold used for classifying a particular sample as 'normal' or 'abnormal'. As described in section 4.3.6, it is a ratio of the likelihood of having a disease given a person is tested positive to the likelihood of having the disease given the person is tested negative, and hence is a measure of the value of the predictor. The overall performance of the predictor for all possible thresholds, however, is the C-index, which is the area under the ROC curve. The specificity, sensitivity, positive predictive value and negative predictive value shown for each model are the values corresponding to the maximum RR value determined for that model.

The p-values for the ROC curve areas (or c-indexes) are also shown. The p-value is the probability that the c-index is equal to 0.5, which is no discrimination ability.

As expected, logistic regression models performed better (due to their better learning performance). Overall, the results for logistic regression show good discrimination performance and show that there is no overfitting in the model building process on the derivation set. This is because the holdout set and validation set performances are almost the same. However, since the confidence intervals for all classifications except 'normal vs abnormal' include c-indexes less than 0.5, we cannot be certain about the reliability of the classification performance. It is likely that this is because of the small data sets used in this thesis, and if a bigger data set was used for derivation and validation of the models, the variance of the performance would be smaller. Also, we observe that the variance is lowest for the biggest data set ('normal vs abnormal')

Table 5.6: Results of applying models developed to independent validation sets for each classification

	ROC area	std dev	C-index p-value	95% conf interval		brier score	max RR	Spec (%)	Sens (%)	PPV (%)	NPV (%)
normal vs abnormal (D = 100, V = 60)											
LR	0.66	0.07	0.02	0.52	0.80	0.25	3.00	15.00	97.00	60.00	80.00
NN	0.63	0.07	0.03	0.49	0.77	0.26	1.92	88.00	47.00	84.00	56.00
normal vs distant (D = 50, V = 30)											
LR	0.68	0.10	0.04	0.48	0.88	0.34	1.94	85.00	53.00	82.00	58.00
NN	0.60	0.10	0.16	0.40	0.80	0.27	1.87	100.00	12.00	100.00	46.00
distant vs imminent (D = 56, V = 34)											
LR	0.66	0.10	0.05	0.47	0.85	0.25	2.89	59.00	82.00	67.00	77.00
NN	0.63	0.10	0.10	0.43	0.83	0.26	1.00	29.00	71.00	50.00	50.00
normal vs imminent (D = 50, V = 30)											
LR	0.59	0.11	0.21	0.37	0.81	0.28	3.20	31.00	94.00	64.00	80.00
NN	0.57	0.11	0.24	0.35	0.79	0.27	2.00	100.00	24.00	100.00	50.00

(LR = logistic regression; NN = neural network)
(D = number of samples in derivation set; V = number of samples in validation set)

and the confidence interval is [0.52, 0.80] which denotes a reasonable classification performance with a c-index of 0.66. For three of the logistic regression models out of four, the p-value is less than 0.05, which means the c-index is significantly different from 0.5 at a 95% significance level.

Using the results from the classification of 'normal vs abnormal', we can conclude that P-wave and PQ segment alternans testing can potentially be a good predictor of PAF (since it can discriminate between normal patients and those with PAF). At the same time, further testing of the model needs to be done on a bigger data set to validate its performance as a useful predictor.

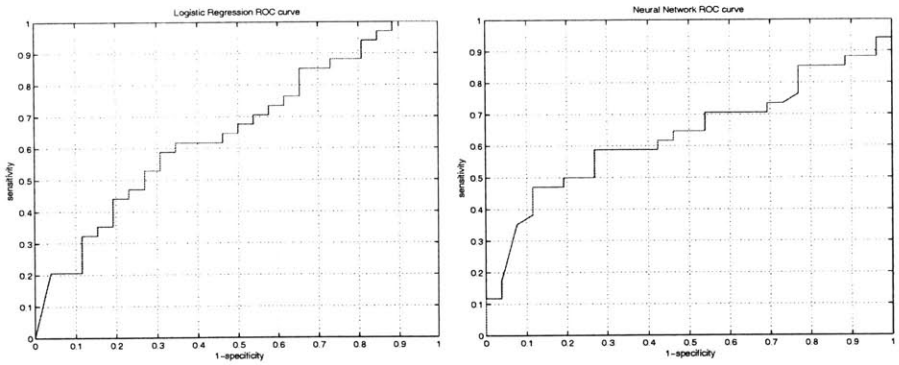

Figure 5-1: ROC curves for the best logistic regression model and best neural network model when run on the independent validation set for 'normal vs abnormal'

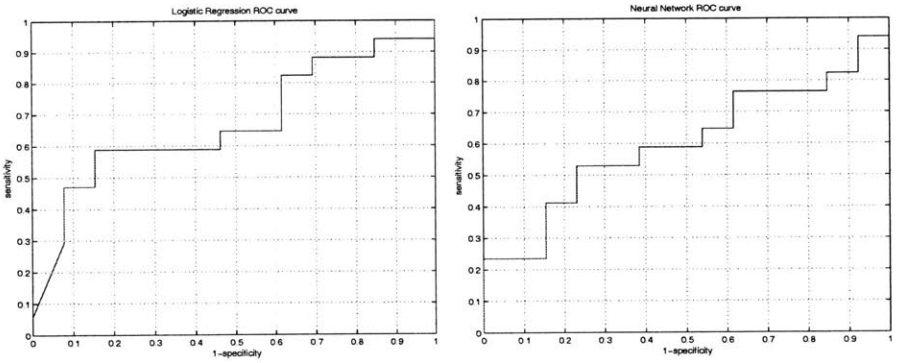

Figure 5-2: ROC curves for the best logistic regression model and best neural network model when run on the independent validation set for 'normal vs distant'

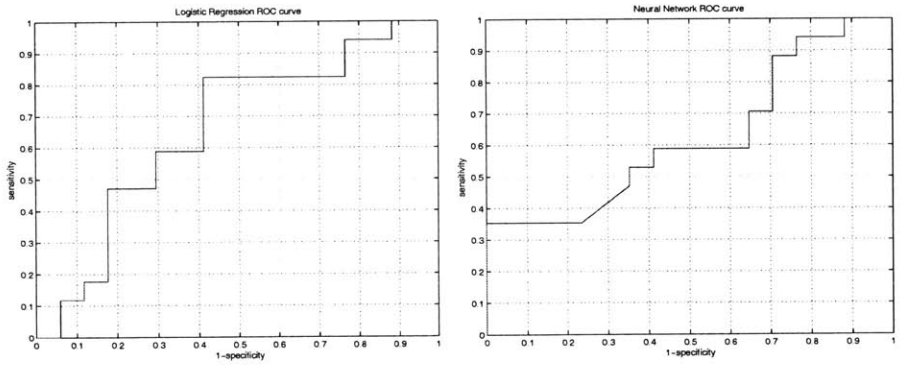

Figure 5-3: ROC curves for the best logistic regression model and best neural network model when run on the independent validation set for 'distant vs imminent'

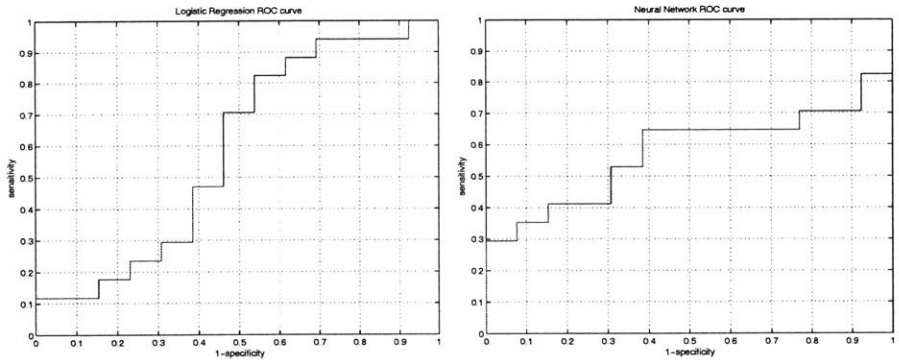

Figure 5-4: ROC curves for the best logistic regression model and best neural network model when run on the independent validation set for 'normal vs imminent'

Chapter 6

Discussion

6.1 Conclusion

In this thesis, predictive models using a small data set (80 patients — 35 normal and 45 PAF) were constructed to classify ECG records as either: normal or PAF; normal or PAF but distant from an episode; distant from PAF or just before PAF; and normal or just before PAF episode.

The problem was divided into four parts in this way to investigate if any of the four classifications can be made, as each would be useful or instructive in its own way. It is quite possible for alternans testing to be a good predictor only in the case when an episode of PAF is imminent, and when an episode is far away, to be unable to distinguish a normal person from a person with PAF.

In this thesis, we demonstrated that alternans testing could potentially be a useful stand-alone ECG based predictor of Paroxysmal Atrial Fibrillation.

It would be a far cry to proclaim that alternans testing is a reliable and error-free predictor of PAF; however, the results of this thesis necessitate a thorough and prospective study of PAF and alternans based prediction. The following section suggests some important possibilities for future work.

6.2 Future work

A large number of ECG records from a large number of patients (both normal and with PAF) has to be collected and the models developed in this thesis need to be applied to a larger ECG database to validate the results.

The ECG used in this study was from 2-channel Holter monitors and as such, the data collected is not very accurate. 16% of the records available were eliminated in this study just because they were not accurate enough to be used for the alternans analysis. The P-wave is a small portion of the ECG with a very small magnitude relative to the rest of the ECG and an accurate P-wave is required for P-wave alternans analysis. For an accurate analysis, ECG signals collected from standard 12-lead ECG monitors need to be used. These signals are not only less noisy than Holter ECG but also have a higher resolution.

The effect and efficacy of drugs administration in managing PAF is an important problem and alternans monitoring can be a useful indicator for testing the efficacy of such drugs. The effect of drugs on alternans levels needs to be tested.

Apart from having records from a larger population, longer records are needed from each patient. The signals used in this thesis were 30 minute duration in length. A one-hour ECG recording, for example, would contain more alternans information and a more conclusive analysis could perhaps be made.

Also, a longer term study needs to be made that monitors PAF patients over a period of time. The relation of alternans levels to frequency of PAF episodes is an important question, that has not been addressed in this thesis, and was beyond the scope. The data from PAF patients that was used in this thesis had no information about the prevalence and frequency of PAF in the patients, which could be a factor in the prominence and incidence of alternans.

At the beginning of this thesis, we mentioned some other techniques that have been tried out for prediction of PAF using ECG, giving encouraging but not reliable results. It is possible that a combination of techniques including alternans testing, frequency of premature atrial complexes, and signal-averaged-ECG P-wave duration,

etc. for example, could produce a more reliable predictor for PAF.

In this thesis, we have implemented a robust algorithm for computing alternans information from ECG signals, and also a framework for analyzing and modeling this data. This provides a base for continuing further research in this area, and investigating most of the questions posed above for future work.

Appendix A

Overall Statistics

Table A.1: P-wave Alternans Channel 0 Statistics

Record	% of SA segments above threshold voltage: 0 uV	2 uV	4 uV	Average Alternans Index	Areas of contiguous SA segments Max	Average	Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
Normal									
mean	7.95	2.66	0.55	2.09	8.05	3.58	2.01	1.67	0.15
median	6.89	0.34	0.00	1.94	5.57	2.64	1.79	1.37	0.10
std dev	5.28	4.23	1.91	1.32	9.43	2.97	0.88	1.04	0.16
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	27.37	20.14	12.23	7.90	51.63	14.52	4.67	4.78	1.00
Abnormal									
mean	7.73	2.81	1.03	2.22	9.42	4.29	1.99	2.03	0.18
median	7.45	0.83	0.00	1.93	5.53	2.89	2.00	1.54	0.10
std dev	4.77	3.88	2.71	1.44	12.23	3.86	0.85	1.54	0.20
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	20.74	13.91	13.91	9.00	75.23	20.14	5.50	7.55	0.99
Distant									
mean	7.43	2.09	0.82	1.90	6.69	3.47	1.84	1.82	0.15
median	6.77	0.00	0.00	1.81	3.16	2.20	2.00	1.23	0.07
std dev	5.26	3.56	2.47	1.05	7.46	3.13	0.70	1.63	0.20
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	20.74	13.91	13.91	5.96	32.96	13.92	4.00	7.55	0.99
Imminent									
mean	8.03	3.53	1.23	2.55	12.15	5.12	2.15	2.24	0.20
median	8.06	2.36	0.00	2.42	6.61	3.85	2.00	1.96	0.13
std dev	4.26	4.09	2.94	1.70	15.22	4.35	0.97	1.44	0.20
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	17.17	13.40	11.34	9.00	75.23	20.14	5.50	6.96	0.93

Table A.2: P-wave Alternans Channel 1 Statistics

Record	% of SA segments above threshold voltage: 0 uV	2 uV	4 uV	Average Alternans Index	Areas of contiguous SA segments Max	Average	Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
Normal									
mean	7.14	1.15	0.14	2.16	5.16	2.57	2.05	1.15	0.09
median	6.38	0.00	0.00	1.84	3.30	1.84	1.86	1.00	0.06
std dev	4.77	2.42	0.80	1.56	4.76	2.14	1.23	0.72	0.09
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	23.16	9.45	6.21	7.40	19.35	11.20	8.00	3.85	0.48
Abnormal									
mean	7.25	2.20	0.91	2.02	7.90	3.80	1.91	1.73	0.14
median	6.91	0.00	0.00	1.93	4.61	2.35	1.83	1.25	0.08
std dev	4.78	3.66	2.26	1.12	9.58	4.53	0.98	1.50	0.16
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	25.19	18.80	11.97	6.02	46.31	26.65	5.50	5.75	0.92
Distant									
mean	6.62	2.01	0.67	1.90	6.29	3.18	1.82	1.58	0.12
median	6.78	0.00	0.00	1.81	3.80	1.98	1.75	0.96	0.07
std dev	4.39	3.23	1.73	1.01	7.86	3.14	0.90	1.38	0.12
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	25.19	12.61	7.73	4.57	42.05	14.05	4.25	5.38	0.51
Imminent									
mean	7.88	2.40	1.16	2.13	9.52	4.42	2.00	1.88	0.16
median	7.38	0.00	0.00	2.00	6.61	2.62	2.00	1.33	0.09
std dev	5.11	4.08	2.68	1.21	10.89	5.55	1.06	1.60	0.18
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	18.80	18.80	11.97	6.02	46.31	26.65	5.50	5.75	0.92

Table A.3: PQ segment Alternans Channel 0 Statistics

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
Normal									
mean	7.96	6.45	4.45	2.62	32.52	12.80	1.71	6.57	0.68
median	6.83	5.71	3.00	2.39	13.59	8.36	1.50	4.15	0.29
std dev	5.82	6.04	5.95	1.91	58.31	21.31	0.79	7.37	1.69
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	37.37	37.37	37.37	10.64	421.86	165.22	4.44	43.64	13.91
Abnormal									
mean	6.85	5.85	3.41	2.58	36.73	17.10	1.76	8.78	0.64
median	6.24	5.03	2.11	2.20	13.79	6.52	1.50	3.81	0.29
std dev	4.32	4.43	3.78	1.85	63.06	25.21	0.85	11.11	1.02
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	23.29	21.92	14.63	11.60	419.11	144.02	5.50	64.01	6.40
Distant									
mean	6.56	5.23	2.80	2.59	33.41	16.73	1.77	9.17	0.54
median	6.09	4.20	1.60	2.19	14.58	6.21	1.50	3.42	0.30
std dev	4.21	4.36	3.25	1.81	64.64	24.93	0.85	13.00	0.99
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	20.74	20.74	10.37	9.67	419.11	144.02	4.67	64.01	6.40
Imminent									
mean	7.14	6.47	4.02	2.57	40.06	17.47	1.75	8.39	0.73
median	6.73	5.88	2.74	2.22	13.68	6.58	1.50	4.12	0.28
std dev	4.46	4.46	4.19	1.92	61.97	25.76	0.86	8.96	1.06
min	0.94	0.00	0.00	0.17	1.06	1.05	1.00	1.05	0.01
max	23.29	21.92	14.63	11.60	234.65	121.50	5.50	41.07	4.39

Table A.4: PQ segment Alternans Channel 1 Statistics

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
Normal									
mean	6.36	4.35	2.34	2.09	15.03	6.59	1.44	3.94	0.32
median	5.22	3.59	1.12	1.92	8.14	4.81	1.33	3.07	0.15
std dev	4.81	4.76	4.29	1.47	28.34	10.16	0.68	4.11	0.79
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	28.95	28.95	28.95	6.68	224.42	77.81	3.44	23.19	6.55
Abnormal									
mean	7.24	5.36	3.10	2.49	37.95	16.29	1.73	7.65	0.59
median	6.62	4.59	1.82	2.17	11.98	5.29	1.59	3.73	0.25
std dev	4.22	4.21	3.64	1.58	82.93	35.04	0.72	11.44	1.22
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	26.67	26.67	13.33	9.91	651.43	267.15	5.14	77.92	10.39
Distant									
mean	7.91	5.75	3.22	2.48	41.17	17.66	1.80	7.63	0.68
median	7.32	4.97	1.74	2.29	13.57	4.90	1.60	3.68	0.25
std dev	4.80	4.83	3.93	1.62	100.14	41.06	0.83	12.39	1.57
min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
max	26.67	26.67	13.33	9.91	651.43	267.15	5.14	77.92	10.39
Imminent									
mean	6.58	4.98	2.98	2.49	34.72	14.92	1.67	7.67	0.50
median	6.25	4.03	2.04	2.06	10.67	5.66	1.50	3.97	0.23
std dev	3.49	3.49	3.37	1.57	62.14	28.17	0.59	10.55	0.72
min	1.06	0.00	0.00	0.36	1.31	1.31	1.00	0.84	0.01
max	14.52	12.90	11.34	6.74	380.32	178.63	3.00	59.54	3.95

Table A.5: T-test results for comparison of set pairs for each variable

p-values for t-test on pairs of ECG alternans data samples

	% of SA segments above threshold voltage:			Alternans Index	Areas of contiguous SA segments		Avg duration SA segs	Avg alternans voltage in SA regions	Avg alternans voltage over 30 min ECG
	0 uV	2 uV	4 uV		Average	Max			
					Abnormal > Normal				
P-wave Ch 0	0.61	0.41	0.11	0.55	0.28	0.22	0.16	0.10	0.05
P-wave Ch 1	0.44	0.02	0.00	0.79	0.75	0.01	0.02	0.02	0.00
PQ Ch 0	0.92	0.77	0.91	0.34	0.55	0.33	0.57	0.13	0.08
PQ Ch 1	0.11	0.08	0.11	0.01	0.05	0.01	0.06	0.01	0.01
					Distant PAF > Normal				
P-wave Ch 0	0.70	0.77	0.26	0.86	0.80	0.79	0.42	0.58	0.27
P-wave Ch 1	0.72	0.05	0.01	0.86	0.84	0.17	0.15	0.11	0.01
PQ Ch 0	0.92	0.88	0.95	0.34	0.54	0.47	0.68	0.18	0.09
PQ Ch 1	0.05	0.06	0.13	0.01	0.09	0.02	0.06	0.02	0.01
					Imminent PAF > Distant PAF				
P-wave Ch 0	0.28	0.04	0.24	0.04	0.02	0.02	0.15	0.02	0.10
P-wave Ch 1	0.11	0.31	0.15	0.19	0.16	0.06	0.07	0.10	0.17
PQ Ch 0	0.27	0.09	0.06	0.55	0.52	0.31	0.19	0.45	0.63
PQ Ch 1	0.93	0.81	0.62	0.80	0.49	0.64	0.75	0.64	0.49
					Imminent PAF > Normal				
P-wave Ch 0	0.47	0.14	0.07	0.22	0.05	0.04	0.07	0.01	0.01
P-wave Ch 1	0.22	0.02	0.00	0.59	0.54	0.00	0.00	0.01	0.00
PQ Ch 0	0.79	0.49	0.66	0.39	0.55	0.26	0.42	0.15	0.12
PQ Ch 1	0.40	0.22	0.20	0.03	0.08	0.01	0.11	0.01	0.00
					Normal > Abnormal				
P-wave Ch 0	0.39	0.59	0.89	0.45	0.72	0.78	0.84	0.90	0.95
P-wave Ch 1	0.56	0.98	1.00	0.21	0.25	0.99	0.98	0.98	1.00
PQ Ch 0	0.08	0.23	0.09	0.66	0.45	0.67	0.43	0.87	0.92
PQ Ch 1	0.89	0.92	0.89	0.99	0.95	0.99	0.94	0.99	0.99
					Normal > Distant PAF				
P-wave Ch 0	0.30	0.23	0.74	0.14	0.20	0.21	0.58	0.42	0.73
P-wave Ch 1	0.28	0.95	0.99	0.14	0.16	0.83	0.85	0.89	0.99
PQ Ch 0	0.08	0.12	0.05	0.66	0.46	0.53	0.32	0.82	0.91
PQ Ch 1	0.95	0.94	0.87	0.99	0.91	0.98	0.94	0.98	0.99
					Distant PAF > Imminent PAF				
P-wave Ch 0	0.72	0.96	0.76	0.96	0.98	0.98	0.85	0.98	0.90
P-wave Ch 1	0.89	0.69	0.85	0.81	0.84	0.94	0.93	0.90	0.83
PQ Ch 0	0.73	0.91	0.94	0.45	0.48	0.69	0.81	0.55	0.37
PQ Ch 1	0.07	0.19	0.38	0.20	0.51	0.36	0.25	0.36	0.51
					Normal > Imminent PAF				
P-wave Ch 0	0.53	0.86	0.93	0.78	0.95	0.96	0.93	0.99	0.99
P-wave Ch 1	0.78	0.98	1.00	0.41	0.46	1.00	1.00	0.99	1.00
PQ Ch 0	0.21	0.51	0.34	0.61	0.45	0.74	0.58	0.85	0.88
PQ Ch 1	0.60	0.78	0.80	0.97	0.92	0.99	0.89	0.99	1.00

Appendix B

Alternans Data

Table B.1: Normal records P-wave Alternans data for Channel 0

Record	% of SA segments above threshold voltage:			Average Alternans	Areas of contiguous SA segments		Average duration of	Average alternans voltage	Average alternans voltage over 30
	0 uV	2 uV	4 uV	Index	Max	Average	SA segments	in SA regions	min ECG record
1a	3.03	0.00	0.00	1.10	1.19	0.57	1.67	0.34	0.01
1b	8.28	0.00	0.00	0.67	0.57	0.26	1.50	0.18	0.01
2a	13.01	0.68	0.00	2.37	2.85	1.44	1.90	0.76	0.10
2b	7.48	0.00	0.00	1.76	2.20	0.94	1.83	0.51	0.04
3a	15.43	0.00	0.00	2.98	7.20	2.25	2.42	0.93	0.14
3b	15.56	0.00	0.00	2.28	8.22	2.12	2.00	1.06	0.16
4a	2.88	2.88	0.00	1.92	5.17	3.62	1.50	2.41	0.07
4b	2.75	0.00	0.00	0.78	1.99	1.48	1.50	0.99	0.03
5a	11.20	0.00	0.00	1.20	3.45	1.76	1.75	1.00	0.11
5b	4.65	3.10	0.00	0.50	4.35	2.49	1.20	2.07	0.10
6a	2.29	0.00	0.00	3.51	1.33	1.33	3.00	0.44	0.01
6b	1.24	0.00	0.00	0.99	0.27	0.26	1.00	0.26	0.00
7a	6.70	0.00	0.00	4.45	5.71	2.61	2.60	1.01	0.07
7b	27.37	5.79	0.00	4.73	13.86	4.97	3.06	1.62	0.44
8a	9.26	0.93	0.00	1.90	2.50	1.16	1.43	0.81	0.07
8b	9.43	0.00	0.00	2.54	1.51	0.48	2.00	0.24	0.02
9a	3.08	0.00	0.00	2.09	0.86	0.68	1.33	0.51	0.02
9b	6.77	0.00	0.00	2.32	1.28	0.85	1.29	0.66	0.04
10a	14.04	10.11	0.00	2.29	31.24	8.09	3.57	2.26	0.32
10b	5.98	0.00	0.00	2.47	5.43	3.96	3.50	1.13	0.07
11a	9.20	9.20	4.29	2.19	13.08	8.56	2.14	4.00	0.37
11b	6.60	1.89	0.00	1.68	6.32	2.48	1.40	1.77	0.12
12a	4.93	0.70	0.00	2.49	4.53	2.72	1.75	1.55	0.08
12b	5.22	0.00	0.00	1.92	4.27	2.17	1.75	1.24	0.06
13a	6.71	6.10	0.61	1.49	13.94	5.20	1.83	2.83	0.19
13b	4.58	1.96	0.00	0.59	6.05	4.72	2.33	2.02	0.09
14a	12.60	3.15	0.00	1.45	8.53	4.18	2.29	1.83	0.23
14b	13.22	0.83	0.00	1.96	10.22	4.33	3.20	1.35	0.18
15a	4.29	3.57	0.00	0.89	6.93	3.23	1.20	2.70	0.12
15b	6.98	6.98	2.33	2.95	25.64	8.74	2.25	3.88	0.27
16a	2.70	0.00	0.00	0.54	1.49	1.40	1.00	1.40	0.04
16b	2.22	1.48	0.00	1.48	3.82	3.51	1.50	2.34	0.05
17a	20.86	20.14	12.23	5.43	51.63	11.54	2.42	4.78	1.00
17b	4.49	0.00	0.00	1.42	2.65	1.97	1.33	1.48	0.07
18a	9.45	9.45	0.79	1.45	11.05	4.30	1.33	3.23	0.30
18b	3.88	3.88	0.00	1.58	8.44	4.40	1.67	2.64	0.10
19a	2.68	0.00	0.00	0.26	0.68	0.60	1.00	0.60	0.02
19b	7.62	0.00	0.00	3.39	3.18	2.00	2.00	1.00	0.08
20a	2.48	0.00	0.00	1.00	2.77	2.06	1.50	1.37	0.03
20b	7.76	0.00	0.00	2.24	5.95	4.04	4.50	0.90	0.07
21a	11.83	3.23	1.08	2.82	5.84	3.81	1.83	2.08	0.25
21b	2.94	2.94	0.98	1.01	6.74	5.44	1.50	3.63	0.11
22a	8.41	0.00	0.00	1.48	2.91	1.83	1.29	1.42	0.12
22b	6.35	0.00	0.00	1.17	2.81	1.83	1.33	1.37	0.09
23a	6.80	2.91	0.00	2.59	11.62	4.92	2.33	2.11	0.14
23b	16.54	16.54	7.87	2.85	43.14	14.52	3.50	4.15	0.69
24a	8.67	2.67	0.00	1.67	9.81	4.85	2.60	1.87	0.16
24b	11.41	5.37	0.00	2.33	21.48	8.98	4.25	2.11	0.24
25a	2.04	0.00	0.00	0.75	1.02	0.94	1.00	0.94	0.02
25b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26a	9.73	9.73	0.00	2.06	15.43	7.23	2.75	2.63	0.26
26b	6.67	3.33	0.00	1.90	5.80	3.36	1.60	2.10	0.14
27a	16.08	0.00	0.00	2.19	6.14	2.35	2.30	1.02	0.16
27b	22.86	0.00	0.00	3.09	11.76	3.47	2.91	1.19	0.27
28a	7.84	5.23	0.00	2.19	11.14	6.56	3.00	2.19	0.17
28b	10.74	10.74	5.37	1.15	19.26	8.21	2.00	4.11	0.44
29a	1.89	0.00	0.00	0.77	1.46	1.25	1.00	1.25	0.02
29b	3.61	0.00	0.00	1.89	1.11	0.83	1.00	0.83	0.03
30a	5.49	0.00	0.00	2.37	3.16	2.14	1.67	1.28	0.07
30b	8.24	0.00	0.00	1.26	2.50	1.50	1.40	1.07	0.09
31a	7.69	3.30	0.00	2.49	5.37	3.47	1.75	1.98	0.15
31b	7.48	4.67	0.93	3.44	15.84	4.88	2.00	2.44	0.18
32a	2.63	0.00	0.00	2.89	1.59	1.35	1.00	1.35	0.04
32b	16.28	13.95	0.00	7.90	27.61	12.08	4.67	2.59	0.42
33a	10.94	0.00	0.00	2.13	6.03	3.37	2.80	1.20	0.13
33b	10.87	0.72	0.00	1.08	6.98	2.67	2.14	1.25	0.14
34a	3.50	0.00	0.00	0.69	3.42	1.67	1.67	1.00	0.04
34b	4.32	0.00	0.00	3.73	2.33	1.46	1.50	0.97	0.04
35a	5.63	1.25	0.00	5.32	8.49	5.47	3.00	1.82	0.10
35b	10.06	7.10	2.37	2.07	10.29	6.71	2.43	2.76	0.28

Table B.2: Normal records P-wave Alternans data for Channel 1

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1a	8.48	0.00	0.00	6.17	4.38	1.35	2.00	0.67	0.06
1b	12.41	8.97	6.21	3.06	14.61	7.70	2.00	3.85	0.48
2a	4.79	0.00	0.00	2.31	1.11	0.50	1.40	0.35	0.02
2b	6.12	0.00	0.00	2.22	3.05	1.51	1.80	0.84	0.05
3a	5.32	0.00	0.00	2.21	3.41	1.19	1.67	0.72	0.04
3b	12.22	0.00	0.00	3.59	4.15	1.70	2.44	0.70	0.09
4a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4b	0.92	0.00	0.00	0.54	0.93	0.93	1.00	0.93	0.01
5a	4.80	0.00	0.00	1.89	1.37	0.79	1.20	0.65	0.03
5b	9.30	0.00	0.00	2.84	3.24	1.39	2.00	0.69	0.06
6a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6b	1.86	0.00	0.00	1.80	2.77	2.77	3.00	0.92	0.02
7a	7.22	0.52	0.00	1.91	3.25	1.36	1.40	0.97	0.07
7b	23.16	1.05	0.00	4.82	9.24	4.44	3.38	1.31	0.30
8a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8b	6.60	0.00	0.00	1.36	0.73	0.45	2.33	0.19	0.01
9a	7.69	0.00	0.00	1.27	1.43	0.75	1.25	0.60	0.05
9b	9.77	0.00	0.00	2.64	2.11	0.76	1.63	0.47	0.05
10a	6.74	0.00	0.00	2.34	5.58	2.17	1.71	1.26	0.09
10b	11.11	0.00	0.00	1.44	2.70	1.79	2.17	0.82	0.09
11a	6.75	6.13	1.23	1.59	7.90	3.77	1.38	2.74	0.19
11b	14.15	0.00	0.00	3.76	9.15	5.06	3.75	1.35	0.19
12a	6.34	0.00	0.00	1.72	4.25	2.07	3.00	0.69	0.04
12b	4.48	0.00	0.00	1.01	0.92	0.69	1.00	0.69	0.03
13a	14.02	1.83	0.00	1.24	5.86	2.85	1.92	1.49	0.21
13b	12.42	9.15	0.00	1.84	14.57	4.79	2.11	2.27	0.28
14a	3.15	0.00	0.00	0.29	1.24	1.10	1.00	1.10	0.03
14b	8.26	0.00	0.00	4.59	9.35	4.07	3.33	1.22	0.10
15a	6.43	2.86	0.00	1.90	9.02	3.33	1.80	1.85	0.12
15b	6.98	6.98	0.00	1.54	8.99	3.47	1.50	2.32	0.16
16a	4.50	0.00	0.00	1.15	3.30	2.58	2.50	1.03	0.05
16b	4.44	2.22	0.00	0.72	5.28	2.70	1.50	1.80	0.08
17a	15.11	3.60	0.00	2.87	12.23	3.92	2.33	1.68	0.25
17b	7.87	0.00	0.00	2.75	6.37	3.52	3.50	1.00	0.08
18a	10.24	9.45	2.36	2.21	14.30	6.60	2.17	3.05	0.31
18b	10.08	6.98	0.00	1.79	15.48	5.91	2.60	2.27	0.23
19a	1.79	0.00	0.00	0.42	0.57	0.55	1.00	0.55	0.01
19b	12.38	0.00	0.00	2.00	3.75	1.46	2.17	0.67	0.08
20a	6.61	0.00	0.00	0.87	1.10	0.68	1.33	0.51	0.03
20b	8.62	3.45	0.00	2.60	10.79	4.57	3.33	1.37	0.12
21a	21.51	3.23	0.00	7.40	9.26	3.49	2.50	1.40	0.30
21b	0.98	0.98	0.00	1.66	2.30	2.30	1.00	2.30	0.02
22a	3.74	0.00	0.00	2.62	2.46	1.63	1.33	1.23	0.05
22b	7.14	0.00	0.00	2.28	5.71	3.45	3.00	1.15	0.08
23a	7.77	0.00	0.00	3.92	11.20	11.20	8.00	1.40	0.11
23b	5.51	3.15	0.00	1.32	4.70	3.70	1.75	2.11	0.12
24a	11.33	0.00	0.00	1.49	3.29	1.78	1.70	1.05	0.12
24b	9.40	5.37	0.00	1.86	14.86	7.53	3.50	2.15	0.20
25a	6.12	0.00	0.00	2.24	4.23	2.97	3.00	0.99	0.06
25b	4.76	0.00	0.00	2.49	2.37	1.89	2.50	0.76	0.04
26a	10.62	0.00	0.00	1.02	7.44	2.77	2.40	1.15	0.12
26b	9.17	0.00	0.00	3.81	3.26	2.14	1.57	1.36	0.12
27a	5.59	0.00	0.00	2.89	2.45	1.27	2.00	0.63	0.04
27b	2.86	0.00	0.00	1.85	0.89	0.69	1.00	0.69	0.02
28a	3.27	0.65	0.00	3.48	7.24	4.23	2.50	1.69	0.06
28b	11.41	0.00	0.00	5.60	19.35	5.76	4.25	1.36	0.15
29a	15.09	3.77	0.00	1.36	8.58	3.60	2.29	1.58	0.24
29b	4.82	0.00	0.00	5.45	3.98	3.98	4.00	0.99	0.05
30a	16.48	0.00	0.00	6.84	18.65	6.96	5.00	1.39	0.23
30b	2.35	0.00	0.00	0.93	1.97	1.56	1.00	1.56	0.04
31a	4.40	0.00	0.00	1.22	1.48	1.09	1.33	0.82	0.04
31b	4.67	0.00	0.00	2.50	5.71	3.37	2.50	1.35	0.06
32a	3.95	0.00	0.00	1.27	0.56	0.46	1.00	0.46	0.02
32b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
33a	2.34	0.00	0.00	0.75	1.85	1.42	1.50	0.95	0.02
33b	5.80	0.00	0.00	1.07	2.10	1.15	1.14	1.00	0.06
34a	2.80	0.00	0.00	0.74	1.60	1.04	2.00	0.52	0.01
34b	5.76	0.00	0.00	1.72	1.81	1.03	1.60	0.64	0.04
35a	5.00	0.00	0.00	1.42	1.64	0.82	1.14	0.72	0.04
35b	1.78	0.00	0.00	1.01	1.92	1.73	1.50	1.15	0.02

Table B.3: Normal records PQ segment Alternans data for Channel 0

Record	% of SA segments above threshold voltage:			Average Alternans	Areas of contiguous SA segments		Average duration of	Average alternans voltage	Average alternans voltage over 30
	0 uV	2 uV	4 uV	Index	Max	Average	SA segments	in SA regions	min ECG record
1a	13.33	0.00	0.00	3.95	4.27	1.14	2.75	0.41	0.06
1b	5.52	0.00	0.00	2.49	0.94	0.45	1.33	0.34	0.02
2a	10.96	0.68	0.00	3.89	4.86	2.41	2.00	1.20	0.13
2b	10.20	0.00	0.00	2.06	5.87	2.37	1.88	1.26	0.13
3a	11.17	3.19	1.60	1.43	13.67	3.71	1.40	2.65	0.30
3b	7.78	6.67	5.56	2.31	36.35	11.56	1.08	10.74	0.84
4a	6.73	1.92	0.00	1.19	3.00	1.72	1.17	1.47	0.10
4b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5a	12.80	12.80	7.20	4.50	49.03	12.60	2.67	4.73	0.60
5b	6.20	6.20	4.65	2.53	28.99	11.45	2.00	5.72	0.35
6a	6.11	3.05	0.00	1.30	6.36	2.36	1.14	2.06	0.13
6b	2.48	0.00	0.00	1.13	3.72	2.01	1.33	1.51	0.04
7a	9.79	9.79	9.79	1.94	154.33	28.08	2.11	13.30	1.30
7b	37.37	37.37	37.37	5.52	421.86	165.22	4.44	37.23	13.91
8a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8b	0.94	0.00	0.00	0.16	0.34	0.34	1.00	0.34	0.00
9a	6.92	1.54	0.00	3.36	8.78	3.68	2.25	1.63	0.11
9b	14.29	3.76	0.00	10.64	13.50	3.55	2.11	1.68	0.24
10a	6.74	6.74	6.74	1.46	209.60	65.46	1.50	43.64	2.94
10b	3.42	3.42	3.42	2.39	11.87	9.21	1.33	6.91	0.24
11a	5.52	5.52	5.52	2.61	54.15	17.89	1.50	11.93	0.66
11b	15.09	15.09	13.21	1.39	62.85	21.60	2.29	9.45	1.43
12a	11.27	11.27	4.93	10.52	41.10	13.46	3.20	4.21	0.47
12b	0.75	0.75	0.00	0.43	3.02	3.02	1.00	3.02	0.02
13a	6.10	6.10	6.10	5.37	20.15	12.90	1.43	9.03	0.55
13b	6.54	6.54	6.54	2.22	17.68	8.80	1.43	6.16	0.40
14a	5.51	5.51	5.51	2.03	48.80	19.69	1.40	14.06	0.78
14b	5.79	5.79	5.79	1.66	33.17	16.71	1.17	14.32	0.83
15a	5.71	5.71	5.71	1.74	34.91	19.00	1.33	14.25	0.81
15b	7.75	7.75	7.75	1.79	53.79	30.87	1.43	21.61	1.67
16a	4.50	3.60	2.70	3.87	11.15	7.92	1.25	6.34	0.29
16b	10.37	9.63	5.93	2.56	23.52	11.42	1.75	6.52	0.68
17a	7.91	7.91	7.91	3.39	33.41	15.93	1.38	11.59	0.92
17b	10.11	6.74	1.12	3.79	8.37	4.54	1.80	2.52	0.26
18a	1.57	1.57	1.57	0.76	10.83	10.35	1.00	10.35	0.16
18b	3.88	3.88	3.88	1.17	14.55	8.86	1.25	7.09	0.27
19a	4.46	2.68	0.00	1.45	3.44	2.24	1.00	2.24	0.10
19b	13.33	7.62	0.00	2.39	5.59	3.12	1.56	2.01	0.27
20a	4.96	4.96	0.00	2.03	5.77	4.48	1.50	2.99	0.15
20b	10.34	10.34	0.86	2.74	12.31	5.62	1.71	3.28	0.34
21a	10.75	10.75	7.53	3.87	20.44	9.07	1.67	5.44	0.59
21b	8.82	8.82	8.82	4.52	64.33	28.20	2.25	12.53	1.11
22a	9.35	9.35	4.67	2.34	45.74	15.49	2.00	7.75	0.72
22b	8.73	8.73	7.94	1.42	65.94	20.72	1.38	15.07	1.32
23a	10.68	10.68	8.74	2.69	46.10	17.35	2.75	6.31	0.67
23b	7.87	7.87	7.87	2.44	55.03	33.47	3.33	10.04	0.79
24a	6.67	6.67	5.33	3.01	31.54	11.55	1.43	8.09	0.54
24b	5.37	5.37	4.70	1.08	15.34	6.97	1.60	4.35	0.23
25a	7.14	5.10	2.04	1.55	9.81	4.72	1.17	4.05	0.29
25b	3.81	3.81	1.90	2.51	7.95	7.87	2.00	3.94	0.15
26a	13.27	13.27	12.39	2.77	30.28	10.78	1.67	6.47	0.86
26b	18.33	18.33	18.33	3.23	57.64	21.62	2.75	7.86	1.44
27a	4.20	3.50	0.00	0.80	4.49	3.15	1.20	2.62	0.11
27b	7.86	5.71	1.43	1.47	11.44	4.76	1.57	3.03	0.24
28a	4.58	4.58	1.96	3.18	12.71	5.57	1.40	3.98	0.18
28b	7.38	7.38	7.38	4.13	29.11	17.42	2.20	7.92	0.58
29a	9.43	8.49	3.77	3.04	9.59	5.06	1.43	3.54	0.33
29b	1.20	0.00	0.00	1.45	1.94	1.94	1.00	1.94	0.02
30a	12.09	9.89	0.00	3.25	12.32	6.05	2.20	2.75	0.33
30b	2.35	0.00	0.00	1.10	1.79	1.40	1.00	1.40	0.03
31a	15.38	13.19	3.30	3.65	26.52	10.79	3.50	3.08	0.47
31b	2.80	1.87	0.00	3.81	5.88	3.82	1.50	2.55	0.07
32a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32b	24.42	24.42	20.93	6.60	77.10	20.80	3.50	5.94	1.45
33a	6.25	6.25	0.78	3.10	6.05	3.91	1.14	3.42	0.21
33b	13.77	12.32	7.97	2.83	46.73	9.41	1.73	5.45	0.75
34a	9.79	9.79	9.09	1.36	76.62	29.42	2.80	10.51	1.03
34b	1.44	1.44	0.00	1.06	3.36	3.11	1.00	3.11	0.04
35a	6.25	5.00	1.25	1.87	9.55	5.42	2.00	2.71	0.17
35b	2.96	2.96	1.78	3.10	15.13	10.24	2.50	4.09	0.12

Table B.4: Normal records PQ segment Alternans data for Channel 1

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1a	12.73	4.85	1.21	4.37	14.23	3.92	1.91	2.05	0.26
1b	13.79	13.79	12.41	6.12	46.14	22.48	2.86	7.87	1.09
2a	6.16	0.00	0.00	2.50	3.90	1.83	1.80	1.02	0.06
2b	11.56	4.08	0.00	3.53	11.56	3.36	1.89	1.78	0.21
3a	3.19	2.13	1.06	2.55	13.25	5.71	1.20	4.76	0.15
3b	6.67	4.44	3.33	1.33	18.30	7.12	1.20	5.93	0.40
4a	5.77	2.88	0.00	1.93	9.02	6.82	3.00	2.27	0.13
4b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5a	12.00	11.20	6.40	1.85	25.94	7.74	1.88	4.13	0.50
5b	6.20	6.20	1.55	1.87	12.47	7.61	2.00	3.80	0.24
6a	4.58	3.82	2.29	3.40	13.10	5.22	1.50	3.48	0.16
6b	2.48	2.48	1.24	0.92	7.85	5.59	1.33	4.19	0.10
7a	8.25	8.25	7.22	4.10	25.71	8.23	1.60	5.14	0.42
7b	28.95	28.95	28.95	4.38	224.42	77.81	3.44	22.64	6.55
8a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8b	1.89	0.00	0.00	2.63	0.16	0.16	2.00	0.08	0.00
9a	4.62	0.00	0.00	1.70	1.73	1.13	1.00	1.13	0.05
9b	5.26	0.00	0.00	2.28	2.04	0.92	1.17	0.78	0.04
10a	4.49	4.49	4.49	1.44	15.00	7.78	1.00	7.78	0.35
10b	5.13	5.13	2.56	2.25	7.20	4.30	1.20	3.59	0.18
11a	4.91	4.91	1.23	6.68	22.65	10.00	2.67	3.75	0.18
11b	4.72	2.83	0.00	1.04	4.37	2.46	1.25	1.97	0.09
12a	3.52	3.52	0.70	1.48	5.52	3.98	1.25	3.18	0.11
12b	2.99	2.99	1.49	1.90	7.42	4.74	1.33	3.55	0.11
13a	1.83	1.83	1.83	1.28	5.73	5.30	1.00	5.30	0.10
13b	3.27	3.27	3.27	1.75	6.51	5.73	1.00	5.73	0.19
14a	4.72	4.72	1.57	0.92	8.22	4.88	1.20	4.07	0.19
14b	4.96	4.96	4.96	2.52	9.22	6.21	1.20	5.17	0.26
15a	3.57	3.57	3.57	3.35	29.17	18.07	1.25	14.46	0.52
15b	3.10	3.10	3.10	2.13	44.07	30.92	1.33	23.19	0.72
16a	6.31	3.60	0.00	2.74	8.90	3.70	1.75	2.12	0.13
16b	11.85	5.93	2.22	4.16	16.59	6.18	2.29	2.70	0.32
17a	15.11	15.11	15.11	2.24	73.29	22.02	2.33	9.44	1.43
17b	5.62	0.00	0.00	1.03	1.98	1.47	1.00	1.47	0.08
18a	7.09	7.09	5.51	3.04	21.69	13.47	3.00	4.49	0.32
18b	7.75	6.98	0.78	0.84	8.05	4.11	1.43	2.88	0.22
19a	5.36	0.00	0.00	0.97	2.00	1.54	1.00	1.54	0.08
19b	7.62	0.00	0.00	0.55	2.29	1.51	1.14	1.32	0.10
20a	3.31	1.65	0.00	2.37	2.59	1.95	1.00	1.95	0.06
20b	5.17	2.59	0.00	3.35	7.69	4.74	2.00	2.37	0.12
21a	2.15	1.08	0.00	0.27	2.25	2.10	1.00	2.10	0.05
21b	1.96	1.96	1.96	0.87	7.46	6.06	1.00	6.06	0.12
22a	8.41	6.54	3.74	1.60	32.17	6.91	1.29	5.38	0.45
22b	4.76	4.76	3.97	2.30	18.69	10.26	1.20	8.55	0.41
23a	7.77	3.88	0.00	0.80	3.98	2.54	1.33	1.90	0.15
23b	3.94	3.94	2.36	1.89	7.08	4.71	1.00	4.71	0.19
24a	1.33	1.33	0.67	0.86	8.22	5.78	1.00	5.78	0.08
24b	7.38	6.71	5.37	1.62	28.36	9.52	1.38	6.92	0.51
25a	9.18	0.00	0.00	5.63	4.79	1.85	1.50	1.24	0.11
25b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26a	14.16	14.16	0.00	2.82	15.48	5.25	1.78	2.96	0.42
26b	13.33	13.33	5.83	2.33	18.64	6.46	1.60	4.04	0.54
27a	4.20	4.20	0.00	2.07	6.28	3.06	1.20	2.55	0.11
27b	17.86	7.86	4.29	2.80	27.17	5.65	2.27	2.48	0.44
28a	9.80	9.80	5.23	4.93	31.73	8.57	2.14	4.00	0.39
28b	8.72	8.72	4.03	2.45	13.01	7.41	1.86	3.99	0.35
29a	7.55	5.66	1.89	0.86	8.49	5.41	1.60	3.38	0.26
29b	12.05	3.61	0.00	3.51	11.65	3.45	2.00	1.73	0.21
30a	4.40	4.40	0.00	3.88	5.43	3.77	1.33	2.83	0.12
30b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31a	4.40	2.20	0.00	0.82	2.73	1.98	1.00	1.98	0.09
31b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32a	5.26	0.00	0.00	1.28	1.91	1.52	1.00	1.52	0.08
32b	5.81	0.00	0.00	0.43	2.98	1.88	1.25	1.50	0.09
33a	3.13	2.34	0.00	0.73	6.92	3.83	1.33	2.87	0.09
33b	10.87	9.42	3.62	2.01	14.62	5.44	1.67	3.26	0.35
34a	4.20	4.20	1.40	1.67	10.22	7.53	2.00	3.77	0.16
34b	0.72	0.00	0.00	0.06	1.93	1.93	1.00	1.93	0.01
35a	8.75	1.25	0.00	2.12	6.98	2.34	1.40	1.67	0.15
35b	6.51	1.78	1.18	2.14	12.88	5.52	1.57	3.51	0.23

Table B.5: Distant PAF records P-wave Alternans data for Channel 0

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1a	12.61	1.68	0.00	1.94	8.00	4.28	2.50	1.71	0.22
2a	9.52	0.00	0.00	1.43	3.63	2.01	2.67	0.75	0.07
3a	4.44	4.44	3.89	1.09	15.69	8.63	1.14	7.55	0.34
4a	8.80	8.80	3.20	2.51	16.01	8.09	2.20	3.68	0.32
5a	1.74	0.00	0.00	0.44	2.91	2.91	2.00	1.45	0.03
6a	3.25	0.00	0.00	5.96	3.16	2.86	2.00	1.43	0.05
7a	10.17	5.65	1.13	1.59	11.86	4.85	2.00	2.42	0.25
8a	2.52	2.52	0.00	0.52	2.72	2.29	1.00	2.29	0.06
9a	6.06	6.06	2.02	3.61	13.63	7.50	2.00	3.75	0.23
10a	1.32	0.66	0.00	0.46	2.60	2.07	1.00	2.07	0.03
11a	4.21	0.00	0.00	1.53	3.32	2.39	2.00	1.20	0.05
12a	3.13	0.00	0.00	1.70	1.52	1.43	1.50	0.95	0.03
13a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14a	12.61	1.68	0.00	1.94	8.00	4.28	2.50	1.71	0.22
15a	10.20	4.08	0.00	3.32	9.11	4.31	2.50	1.73	0.18
16a	8.00	0.00	0.00	2.03	2.90	1.59	1.75	0.91	0.07
17a	7.19	0.00	0.00	1.62	2.71	1.52	1.83	0.83	0.06
18a	17.68	13.26	0.55	4.01	19.17	5.84	2.13	2.74	0.48
19a	8.57	0.00	0.00	1.80	1.92	1.25	1.50	0.83	0.07
20a	9.09	4.04	0.00	1.94	6.94	3.43	1.80	1.91	0.17
21a	2.29	0.00	0.00	2.04	1.25	1.15	1.00	1.15	0.03
22a	4.21	0.00	0.00	1.26	2.15	1.26	1.33	0.95	0.04
23a	2.40	0.00	0.00	1.64	2.29	1.84	1.50	1.23	0.03
24a	20.62	7.22	6.19	3.10	28.65	10.81	2.86	3.78	0.78
25a	6.90	1.15	0.00	0.86	2.42	2.01	1.50	1.34	0.09
26a	8.55	0.00	0.00	1.66	5.68	2.34	2.50	0.94	0.08
27a	4.49	0.00	0.00	1.40	2.48	1.48	1.33	1.11	0.05
28a	9.52	0.00	0.00	1.90	6.49	2.15	2.40	0.90	0.09
29a	4.69	0.00	0.00	2.30	2.21	1.39	1.20	1.16	0.05
30a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31a	2.47	0.00	0.00	1.30	2.20	2.20	2.00	1.10	0.03
32a	7.35	5.88	0.00	3.00	9.53	6.85	2.50	2.74	0.20
33a	5.56	0.00	0.00	1.67	3.29	1.99	1.25	1.59	0.09
34a	1.96	0.00	0.00	1.43	1.97	1.97	2.00	0.98	0.02
35a	7.78	0.00	0.00	2.33	1.81	1.04	1.75	0.59	0.05
36a	17.89	0.00	0.00	1.81	5.20	2.20	1.70	1.29	0.23
37a	20.74	0.00	0.00	2.33	6.79	1.76	2.15	0.82	0.17
38a	13.91	13.91	13.91	2.12	32.96	12.59	1.78	7.08	0.99
39a	6.77	6.77	6.02	2.06	24.86	13.92	2.25	6.19	0.42
40a	14.81	6.17	0.00	1.98	7.50	3.87	2.00	1.94	0.29
41a	3.67	0.00	0.00	1.48	2.58	2.56	2.00	1.28	0.05
42a	5.32	0.00	0.00	1.86	2.77	2.04	1.67	1.22	0.07
43a	3.19	0.00	0.00	1.19	1.47	1.20	1.50	0.80	0.03
44a	5.26	0.00	0.00	2.67	3.12	3.12	4.00	0.78	0.04
45a	12.93	0.00	0.00	2.65	5.36	2.72	2.50	1.09	0.14

Table B.6: Distant PAF records P-wave Alternans data for Channel 1

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1a	5.88	5.88	2.52	1.60	10.91	5.26	1.40	3.76	0.22
2a	6.55	0.00	0.00	1.32	2.37	1.13	1.83	0.62	0.04
3a	8.33	6.67	0.00	2.11	17.39	4.66	1.88	2.49	0.21
4a	5.60	5.60	0.00	1.69	8.30	6.47	2.33	2.77	0.16
5a	2.61	1.74	0.00	0.22	3.58	2.79	1.50	1.86	0.05
6a	8.94	1.63	0.00	2.66	7.48	3.39	2.20	1.54	0.14
7a	6.78	6.78	3.95	3.30	27.33	14.05	3.00	4.68	0.32
8a	12.61	12.61	3.36	3.17	20.62	10.90	3.00	3.63	0.46
9a	7.07	5.05	0.00	3.03	11.22	8.44	3.50	2.41	0.17
10a	5.92	3.29	0.00	1.38	6.55	4.43	2.25	1.97	0.12
11a	8.42	0.00	0.00	2.52	6.16	2.71	2.00	1.35	0.11
12a	12.50	0.00	0.00	2.35	4.08	1.64	1.71	0.96	0.12
13a	7.55	7.55	3.77	1.55	10.19	6.08	1.60	3.80	0.29
14a	5.88	5.88	2.52	1.60	10.91	5.26	1.40	3.76	0.22
15a	8.16	8.16	6.12	4.57	12.23	8.15	1.60	5.09	0.42
16a	9.14	0.00	0.00	2.26	3.41	1.39	2.29	0.61	0.06
17a	3.92	0.00	0.00	1.85	4.91	2.61	2.00	1.30	0.05
18a	9.39	9.39	7.73	3.43	42.05	10.17	1.89	5.38	0.51
19a	2.86	0.00	0.00	2.16	1.95	1.26	1.50	0.84	0.02
20a	6.06	0.00	0.00	1.36	2.08	1.41	1.50	0.94	0.06
21a	8.40	0.76	0.00	1.30	3.80	2.71	1.83	1.48	0.12
22a	8.42	0.00	0.00	0.60	0.67	0.52	1.00	0.52	0.04
23a	2.40	0.00	0.00	1.96	2.26	1.52	1.50	1.02	0.02
24a	8.25	5.15	0.00	2.46	9.23	5.70	2.67	2.14	0.18
25a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
26a	11.11	0.00	0.00	2.27	1.74	1.24	1.63	0.76	0.08
27a	1.12	0.00	0.00	1.58	0.50	0.50	1.00	0.50	0.01
28a	7.94	0.00	0.00	3.51	2.51	1.05	2.00	0.53	0.04
29a	7.03	0.00	0.00	3.68	3.58	1.57	1.80	0.87	0.06
30a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31a	7.41	0.00	0.00	2.16	3.84	2.25	3.00	0.75	0.06
32a	5.15	2.94	0.00	1.71	6.98	3.80	1.75	2.17	0.11
33a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34a	7.84	0.00	0.00	1.28	2.10	1.20	1.33	0.90	0.07
35a	5.56	0.00	0.00	1.81	0.89	0.53	1.25	0.43	0.02
36a	4.21	0.00	0.00	1.24	0.66	0.55	1.00	0.55	0.02
37a	25.19	0.00	0.00	2.19	9.12	3.35	4.25	0.79	0.20
38a	0.87	0.00	0.00	0.84	1.98	1.98	1.00	1.98	0.02
39a	9.77	0.00	0.00	2.93	3.82	1.82	1.44	1.26	0.12
40a	4.94	1.23	0.00	1.91	4.69	2.98	2.00	1.49	0.07
41a	11.93	0.00	0.00	1.72	2.95	1.76	2.60	0.68	0.08
42a	1.06	0.00	0.00	1.29	0.38	0.38	1.00	0.38	0.00
43a	4.26	0.00	0.00	1.56	3.18	3.18	4.00	0.80	0.03
44a	9.21	0.00	0.00	2.77	3.86	1.66	2.33	0.71	0.07
45a	1.72	0.00	0.00	0.66	0.62	0.57	1.00	0.57	0.01

Table B.7: Distant PAF records PQ segment Alternans data for Channel 0

Record	% of SA segments above threshold voltage:			Average Alternans	Areas of contiguous SA segments		Average duration of	Average alternans voltage	Average alternans voltage over 30
	0 uV	2 uV	4 uV	Index	Max	Average	SA segments	in SA regions	min ECG record
1a	4.20	4.20	4.20	6.89	81.85	50.68	2.50	20.27	0.85
2a	8.33	0.00	0.00	3.03	3.83	1.38	1.75	0.79	0.07
3a	10.00	10.00	10.00	4.72	419.11	144.02	2.25	64.01	6.40
4a	8.80	8.80	8.80	3.20	47.59	27.96	1.22	22.87	2.01
5a	6.09	6.09	5.22	1.40	18.11	12.76	2.33	5.47	0.33
6a	8.13	8.13	4.88	1.64	28.66	9.22	2.00	4.61	0.37
7a	1.69	1.69	1.69	2.94	104.37	67.68	1.50	45.12	0.76
8a	6.72	6.72	6.72	1.95	42.92	26.41	2.00	13.21	0.89
9a	3.03	3.03	3.03	1.77	37.50	24.02	1.50	16.01	0.49
10a	2.63	2.63	2.63	2.80	44.91	26.67	2.00	13.33	0.35
11a	4.21	3.16	0.00	2.19	5.90	3.42	1.33	2.56	0.11
12a	4.17	1.04	0.00	2.14	2.90	2.11	1.00	2.11	0.09
13a	6.60	6.60	6.60	2.52	59.20	39.91	1.75	22.81	1.51
14a	4.20	4.20	4.20	6.89	81.85	50.68	2.50	20.27	0.85
15a	6.12	6.12	6.12	1.39	18.81	11.83	1.50	7.89	0.48
16a	9.14	6.86	2.29	2.30	9.93	4.43	1.33	3.32	0.30
17a	3.92	1.31	0.00	1.50	4.32	2.77	1.50	1.85	0.07
18a	1.66	1.66	1.66	0.74	49.07	42.66	1.00	42.66	0.71
19a	3.81	0.00	0.00	0.99	1.69	1.44	1.00	1.44	0.06
20a	5.05	5.05	0.00	3.60	10.84	7.06	2.50	2.82	0.14
21a	2.29	2.29	0.00	1.39	7.25	5.13	1.50	3.42	0.08
22a	5.26	3.16	0.00	2.15	5.00	2.78	1.25	2.23	0.12
23a	1.60	1.60	1.60	0.29	4.23	4.21	1.00	4.21	0.07
24a	5.15	5.15	3.09	2.62	36.10	20.85	2.50	8.34	0.43
25a	12.64	9.20	3.45	1.47	15.66	5.84	1.83	3.18	0.40
26a	5.13	3.42	0.00	1.73	4.96	2.78	1.20	2.32	0.12
27a	15.73	15.73	0.00	6.01	25.11	13.16	4.67	2.82	0.44
28a	8.73	8.73	7.14	2.21	20.75	11.55	2.20	5.25	0.46
29a	3.13	2.34	1.56	1.51	12.28	5.31	1.33	3.98	0.12
30a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31a	6.17	3.70	0.00	3.47	3.23	2.31	1.00	2.31	0.14
32a	2.94	2.94	0.00	0.85	5.87	4.09	1.33	3.07	0.09
33a	3.33	2.22	1.11	2.33	4.82	3.52	1.00	3.52	0.12
34a	1.96	1.96	0.00	1.70	3.52	2.98	1.00	2.98	0.06
35a	8.89	1.11	0.00	1.70	4.39	2.60	1.60	1.62	0.14
36a	12.63	9.47	3.16	2.65	16.74	6.21	2.00	3.11	0.39
37a	20.74	20.74	10.37	9.67	52.46	18.86	4.67	4.04	0.84
38a	6.09	6.09	6.09	2.11	27.22	21.89	2.33	9.38	0.57
39a	7.52	7.52	7.52	3.41	102.22	27.29	1.67	16.37	1.23
40a	7.41	6.17	1.23	1.73	7.46	4.49	1.50	2.99	0.22
41a	10.09	4.59	0.00	2.44	8.14	2.81	1.38	2.04	0.21
42a	7.45	7.45	1.06	3.22	14.58	7.43	2.33	3.19	0.24
43a	6.38	2.13	0.00	1.58	2.58	1.93	1.00	1.93	0.12
44a	9.21	3.95	0.00	2.23	9.81	4.74	2.33	2.03	0.19
45a	16.38	16.38	10.34	3.39	35.68	12.98	2.71	4.78	0.78

Table B.8: Distant PAF records PQ segment Alternans data for Channel 1

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1a	10.92	10.92	10.92	4.45	127.08	49.80	2.60	19.15	2.09
2a	4.76	0.60	0.00	2.37	4.30	2.42	2.00	1.21	0.06
3a	13.33	13.33	13.33	3.94	651.43	267.15	3.43	77.92	10.39
4a	8.80	8.80	8.80	3.41	71.36	21.61	1.38	15.72	1.38
5a	8.70	8.70	8.70	5.27	69.57	36.55	2.50	14.62	1.27
6a	7.32	7.32	7.32	2.17	30.25	13.79	2.25	6.13	0.45
7a	1.13	1.13	1.13	0.23	22.04	18.39	1.00	18.39	0.21
8a	6.72	5.88	3.36	0.68	14.30	4.90	1.33	3.68	0.25
9a	7.07	7.07	7.07	1.51	16.30	11.48	1.75	6.56	0.46
10a	4.61	4.61	4.61	3.73	14.54	7.00	1.40	5.00	0.23
11a	8.42	8.42	3.16	1.78	7.48	4.61	1.14	4.04	0.34
12a	8.33	3.13	0.00	3.59	2.99	2.08	1.14	1.82	0.15
13a	6.60	6.60	6.60	3.44	130.37	71.46	3.50	20.42	1.35
14a	10.92	10.92	10.92	4.45	127.08	49.80	2.60	19.15	2.09
15a	3.06	3.06	3.06	2.39	34.13	19.69	1.50	13.13	0.40
16a	4.00	0.57	0.00	1.22	4.92	2.45	1.75	1.40	0.06
17a	4.58	4.58	3.92	2.74	22.66	12.54	1.75	7.17	0.33
18a	4.97	4.97	4.97	1.00	78.04	39.81	1.80	22.11	1.10
19a	6.67	1.90	1.90	2.77	34.46	8.33	1.40	5.95	0.40
20a	16.16	13.13	3.03	2.84	13.64	4.46	1.60	2.79	0.45
21a	6.11	5.34	2.29	1.32	9.53	3.91	1.14	3.42	0.21
22a	4.21	0.00	0.00	1.37	1.62	1.17	1.33	0.87	0.04
23a	3.20	3.20	1.60	2.18	11.05	5.81	1.33	4.36	0.14
24a	10.31	10.31	8.25	3.06	129.88	32.09	2.00	16.05	1.65
25a	5.75	2.30	0.00	2.86	6.21	4.12	2.50	1.65	0.09
26a	7.69	0.00	0.00	1.65	2.86	1.54	1.13	1.37	0.11
27a	7.87	3.37	0.00	1.64	5.15	2.72	1.40	1.95	0.15
28a	14.29	3.97	0.00	3.05	7.95	3.18	1.80	1.77	0.25
29a	3.91	3.91	3.91	3.64	19.05	9.39	1.67	5.63	0.22
30a	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31a	7.41	6.17	0.00	0.79	6.66	4.07	1.50	2.72	0.20
32a	8.09	7.35	3.68	2.26	9.77	5.88	1.57	3.74	0.30
33a	5.56	4.44	0.00	1.65	6.53	3.46	1.25	2.76	0.15
34a	13.73	5.88	0.00	2.29	13.57	4.42	2.00	2.21	0.30
35a	15.56	8.89	1.11	1.79	7.32	3.23	1.27	2.54	0.39
36a	5.26	0.00	0.00	1.55	3.19	1.94	1.25	1.56	0.08
37a	26.67	26.67	13.33	9.91	61.01	21.38	5.14	4.16	1.11
38a	3.48	3.48	1.74	3.15	13.60	8.75	2.00	4.38	0.15
39a	9.02	7.52	0.00	2.31	11.79	4.73	1.71	2.76	0.25
40a	11.11	11.11	6.17	2.14	14.78	5.28	1.29	4.11	0.46
41a	3.67	0.92	0.00	1.26	2.95	2.07	1.33	1.55	0.06
42a	3.19	1.06	0.00	0.90	2.29	1.58	1.00	1.58	0.05
43a	15.96	4.26	0.00	3.12	8.37	3.39	2.14	1.58	0.25
44a	9.21	5.26	0.00	1.38	6.07	4.35	2.33	1.86	0.17
45a	7.76	7.76	0.00	2.51	14.36	8.00	3.00	2.67	0.21

Table B.9: Imminent PAF records P-wave Alternans data for Channel 0

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1b	2.36	1.57	0.00	1.63	2.48	2.00	1.00	2.00	0.05
2b	10.67	0.00	0.00	3.17	5.49	3.05	3.20	0.95	0.10
3b	7.18	7.18	2.21	1.69	21.63	13.17	2.60	5.06	0.36
4b	13.00	13.00	10.00	1.84	29.90	20.14	3.25	6.20	0.81
5b	9.09	1.65	0.00	3.72	10.60	4.14	2.75	1.51	0.14
6b	8.16	0.00	0.00	2.62	3.85	1.61	2.00	0.81	0.07
7b	4.97	2.48	0.62	0.92	12.38	4.36	2.00	2.18	0.11
8b	7.69	7.69	0.85	2.98	14.92	6.89	2.25	3.06	0.24
9b	2.42	2.42	0.81	0.86	5.90	5.08	1.50	3.39	0.08
10b	12.59	9.09	2.80	2.76	23.31	9.07	3.00	3.02	0.38
11b	7.46	1.49	0.00	2.94	4.08	2.80	1.67	1.68	0.13
12b	5.49	0.00	0.00	0.84	2.13	1.29	1.25	1.03	0.06
13b	12.00	12.00	7.20	9.00	41.09	8.55	1.88	4.56	0.55
14b	3.15	2.36	0.00	2.29	4.29	2.87	1.33	2.15	0.07
15b	6.78	0.85	0.00	2.51	6.09	3.13	2.00	1.56	0.11
16b	10.34	0.00	0.00	1.89	4.38	1.37	1.80	0.76	0.08
17b	4.96	0.00	0.00	2.79	5.56	2.37	2.33	1.01	0.05
18b	7.32	6.50	0.00	3.82	12.76	8.36	3.00	2.79	0.20
19b	9.00	0.00	0.00	4.28	9.44	3.97	3.00	1.32	0.12
20b	6.43	0.00	0.00	2.69	4.53	2.60	1.80	1.45	0.09
21b	17.17	1.01	0.00	1.92	7.03	3.21	2.43	1.32	0.23
22b	9.62	0.00	0.00	2.01	5.72	2.77	2.00	1.38	0.13
23b	1.42	0.00	0.00	0.48	1.12	1.11	1.00	1.11	0.02
24b	12.12	10.10	8.08	5.00	36.89	10.09	2.40	4.21	0.51
25b	13.21	2.83	0.00	0.90	9.94	2.98	1.75	1.70	0.22
26b	4.17	3.47	0.00	0.95	3.11	2.64	1.00	2.64	0.11
27b	9.01	2.70	0.00	3.81	7.78	3.85	2.00	1.93	0.17
28b	7.43	0.00	0.00	0.95	1.86	1.16	1.22	0.95	0.07
29b	13.87	12.14	9.25	5.37	61.46	13.73	3.00	4.58	0.64
30b	8.51	6.38	0.00	2.42	4.60	2.94	1.33	2.21	0.19
31b	2.35	0.00	0.00	0.91	1.27	1.27	1.00	1.27	0.03
32b	8.86	2.53	1.27	0.73	7.38	4.59	2.33	1.97	0.17
33b	4.08	3.06	0.00	4.74	4.68	3.16	1.33	2.37	0.10
34b	1.06	0.00	0.00	1.36	1.00	1.00	1.00	1.00	0.01
35b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
36b	2.50	2.50	0.00	0.58	5.56	5.56	2.00	2.78	0.07
37b	14.77	7.38	0.00	2.93	17.42	6.39	3.14	2.03	0.30
38b	7.48	6.54	0.93	5.19	13.82	8.72	2.67	3.27	0.24
39b	14.12	5.88	0.00	3.35	11.85	6.22	3.00	2.07	0.29
40b	13.40	13.40	11.34	4.37	75.23	18.09	2.60	6.96	0.93
41b	3.36	1.68	0.00	1.38	3.74	2.62	1.33	1.96	0.07
42b	8.06	0.81	0.00	1.78	11.03	5.27	3.33	1.58	0.13
43b	8.06	8.06	0.00	1.23	6.61	3.86	1.67	2.32	0.19
44b	15.07	0.00	0.00	3.84	13.08	6.88	5.50	1.25	0.19
45b	10.62	0.00	0.00	3.32	9.61	5.53	4.00	1.38	0.15

Table B.10: Imminent PAF records P-wave Alternans data for Channel 1

Record	% of SA segments above threshold voltage:			Average Alternans Index	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV		Max	Average			
1b	3.15	1.57	0.00	0.75	4.53	2.81	1.33	2.11	0.07
2b	8.67	0.00	0.00	2.15	3.00	1.70	2.60	0.65	0.06
3b	4.42	2.76	0.00	2.53	6.65	3.43	1.33	2.57	0.11
4b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5b	12.40	4.96	0.00	3.28	14.52	4.68	2.50	1.87	0.23
6b	6.12	4.08	2.04	0.91	12.16	4.64	1.50	3.09	0.19
7b	4.35	4.35	4.35	2.05	11.80	6.44	1.17	5.52	0.24
8b	18.80	18.80	11.97	2.50	29.24	15.40	3.14	4.90	0.92
9b	5.65	0.00	0.00	1.72	3.55	2.31	1.40	1.65	0.09
10b	6.29	0.00	0.00	2.75	7.92	4.47	3.00	1.49	0.09
11b	14.18	1.49	0.00	1.50	7.99	3.68	2.11	1.74	0.25
12b	18.68	0.00	0.00	3.60	9.55	4.18	4.25	0.98	0.18
13b	5.60	5.60	4.00	4.18	37.30	19.86	3.50	5.67	0.32
14b	3.15	2.36	0.00	1.27	6.61	4.45	2.00	2.22	0.07
15b	9.32	9.32	5.93	2.18	17.26	7.14	1.57	4.55	0.42
16b	5.17	0.00	0.00	2.25	1.89	1.37	2.25	0.61	0.03
17b	4.96	0.00	0.00	3.37	6.57	2.77	2.33	1.19	0.06
18b	8.94	8.94	5.69	3.28	33.65	10.93	2.20	4.97	0.44
19b	8.00	5.00	3.00	2.68	9.63	4.99	1.60	3.12	0.25
20b	8.57	0.00	0.00	2.00	5.40	1.82	2.00	0.91	0.08
21b	6.06	0.00	0.00	1.29	1.99	1.49	1.20	1.24	0.08
22b	9.62	0.00	0.00	1.52	3.26	1.83	2.50	0.73	0.07
23b	0.71	0.00	0.00	1.20	1.39	1.39	1.00	1.39	0.01
24b	11.11	11.11	7.07	6.02	46.31	26.65	5.50	4.85	0.54
25b	11.32	0.00	0.00	2.00	3.57	1.31	2.00	0.65	0.07
26b	11.81	0.00	0.00	1.96	9.16	3.59	2.43	1.48	0.17
27b	18.02	2.70	0.00	3.12	14.96	3.78	2.22	1.70	0.31
28b	3.38	0.00	0.00	0.73	0.58	0.51	1.00	0.51	0.02
29b	8.09	5.78	0.00	4.46	20.44	5.71	2.33	2.45	0.20
30b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
31b	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32b	3.80	0.00	0.00	1.54	1.32	1.19	1.00	1.19	0.05
33b	3.06	0.00	0.00	1.20	2.54	1.84	1.50	1.23	0.04
34b	9.57	0.00	0.00	1.50	6.71	2.22	2.25	0.99	0.09
35b	16.88	0.00	0.00	2.77	5.43	2.05	3.25	0.63	0.11
36b	5.00	0.00	0.00	0.90	2.83	2.23	2.00	1.12	0.06
37b	7.38	0.00	0.00	1.68	5.26	2.62	1.83	1.43	0.11
38b	17.76	0.00	0.00	2.97	7.08	2.31	3.17	0.73	0.13
39b	2.35	0.00	0.00	1.83	0.77	0.67	1.00	0.67	0.02
40b	10.31	10.31	8.25	3.44	35.80	19.18	3.33	5.75	0.59
41b	8.40	0.84	0.00	3.27	8.74	3.32	2.50	1.33	0.11
42b	6.45	0.00	0.00	2.33	2.37	1.31	1.60	0.82	0.05
43b	14.52	8.06	0.00	2.54	11.19	3.72	1.80	2.07	0.30
44b	2.74	0.00	0.00	0.90	0.79	0.60	1.00	0.60	0.02
45b	9.73	0.00	0.00	1.90	6.61	2.38	1.83	1.30	0.13

Table B.11: Imminent PAF records PQ segment Alternans data for Channel 0

Record	% of SA segments above threshold voltage:			Average Alternans	Areas of contiguous SA segments		Average duration of	Average alternans voltage	Average alternans voltage over 30
	0 uV	2 uV	4 uV	Index	Max	Average	SA segments	in SA regions	min ECG record
1b	3.94	3.94	3.94	2.01	6.62	5.27	1.00	5.27	0.21
2b	1.33	0.00	0.00	3.46	1.06	1.05	1.00	1.05	0.01
3b	8.84	8.84	8.84	4.03	232.25	82.15	2.00	41.07	3.63
4b	13.00	13.00	13.00	4.51	151.28	48.26	1.86	25.98	3.38
5b	2.48	1.65	0.83	1.41	4.52	3.42	1.00	3.42	0.08
6b	10.20	8.16	4.08	1.30	16.47	4.41	1.43	3.08	0.31
7b	8.07	8.07	6.83	3.20	187.83	41.43	1.86	22.31	1.80
8b	11.11	11.11	11.11	4.04	166.55	37.72	1.44	26.12	2.90
9b	10.48	10.48	10.48	2.50	75.65	39.84	2.17	18.39	1.93
10b	3.50	3.50	3.50	0.99	10.67	8.29	1.00	8.29	0.29
11b	9.70	9.70	9.70	2.62	55.10	16.35	1.44	11.32	1.10
12b	2.20	1.10	0.00	5.63	5.16	5.16	2.00	2.58	0.06
13b	12.00	12.00	12.00	2.12	35.16	14.29	1.50	9.53	1.14
14b	6.30	6.30	4.72	2.27	23.26	7.48	1.14	6.55	0.41
15b	1.69	1.69	1.69	0.84	9.15	7.04	1.00	7.04	0.12
16b	7.47	2.87	1.15	1.69	16.49	5.16	1.44	3.57	0.27
17b	9.22	1.42	0.00	2.43	6.27	2.46	1.44	1.70	0.16
18b	14.63	14.63	14.63	3.70	149.20	90.09	3.00	30.03	4.39
19b	8.00	8.00	5.00	2.43	59.48	25.63	1.60	16.02	1.28
20b	5.00	4.29	0.71	3.96	7.98	4.24	1.40	3.03	0.15
21b	4.04	3.03	0.00	1.65	4.46	2.92	1.33	2.19	0.09
22b	6.73	5.77	0.96	1.98	11.37	6.40	2.33	2.74	0.18
23b	2.13	2.13	0.71	0.95	8.06	5.47	1.50	3.65	0.08
24b	13.13	13.13	9.09	1.32	18.20	8.94	1.86	4.81	0.63
25b	0.94	0.94	0.00	1.90	2.83	2.83	1.00	2.83	0.03
26b	9.03	8.33	2.08	1.82	15.79	6.41	2.17	2.96	0.27
27b	3.60	3.60	3.60	4.93	58.17	58.17	4.00	14.54	0.52
28b	2.70	2.70	2.70	0.17	10.66	7.06	1.00	7.06	0.19
29b	5.20	5.20	5.20	1.54	43.29	19.12	1.50	12.75	0.66
30b	10.64	6.38	2.13	2.22	7.16	4.18	1.25	3.34	0.36
31b	2.35	2.35	0.00	1.15	3.08	2.57	1.00	2.57	0.06
32b	2.53	2.53	0.00	0.70	6.46	6.46	2.00	3.23	0.08
33b	10.20	10.20	9.18	3.28	29.37	15.96	2.50	6.38	0.65
34b	7.45	7.45	1.06	2.99	14.00	5.33	1.75	3.04	0.23
35b	3.90	3.90	0.00	0.26	3.53	2.68	1.00	2.68	0.10
36b	5.00	5.00	0.00	1.49	5.36	3.48	1.33	2.61	0.13
37b	4.03	4.03	3.36	2.66	12.34	8.12	2.00	4.06	0.16
38b	9.35	8.41	0.93	2.28	13.89	7.54	2.50	3.01	0.28
39b	5.88	5.88	3.53	1.21	9.05	5.48	1.00	5.48	0.32
40b	11.34	11.34	11.34	11.60	234.65	121.50	5.50	22.09	2.51
41b	6.72	6.72	3.36	2.01	13.68	6.58	1.60	4.12	0.28
42b	10.48	9.68	0.00	2.60	10.66	6.38	2.17	2.94	0.31
43b	9.68	8.06	4.84	3.15	24.71	9.80	2.00	4.90	0.47
44b	23.29	21.92	2.74	5.85	17.26	8.56	2.83	3.02	0.70
45b	1.77	1.77	1.77	0.76	4.45	4.33	1.00	4.33	0.08

Table B.12: Imminent PAF records PQ segment Alternans data for Channel 1

Record	% of SA segments above threshold voltage:			Average Alternans	Areas of contiguous SA segments		Average duration of SA segments	Average alternans voltage in SA regions	Average alternans voltage over 30 min ECG record
	0 uV	2 uV	4 uV	Index	Max	Average			
1b	3.94	3.94	3.15	0.95	54.15	17.14	1.25	13.71	0.54
2b	13.33	0.00	0.00	1.27	6.69	2.10	2.50	0.84	0.11
3b	6.63	6.63	6.63	3.42	380.32	178.63	3.00	59.54	3.95
4b	8.00	8.00	8.00	0.66	75.61	24.07	1.60	15.04	1.20
5b	6.61	4.96	2.48	0.97	18.87	5.30	1.33	3.97	0.26
6b	4.08	4.08	4.08	0.76	8.75	6.23	1.00	6.23	0.25
7b	3.11	3.11	3.11	2.56	27.55	14.95	1.25	11.96	0.37
8b	5.13	5.13	5.13	4.05	91.92	50.76	3.00	16.92	0.87
9b	4.03	4.03	2.42	3.14	6.16	4.45	1.00	4.45	0.18
10b	9.09	9.09	6.29	4.26	48.67	12.43	2.17	5.74	0.52
11b	9.70	9.70	8.96	2.12	34.18	12.28	1.30	9.44	0.92
12b	10.99	6.59	0.00	2.05	12.16	3.39	1.43	2.37	0.26
13b	11.20	11.20	11.20	6.74	48.77	25.99	1.75	14.85	1.66
14b	2.36	2.36	2.36	3.73	58.47	32.49	1.50	21.66	0.51
15b	5.08	5.08	3.39	1.48	14.13	8.55	1.20	7.13	0.36
16b	4.60	1.72	1.15	1.34	10.67	3.72	1.60	2.33	0.11
17b	4.26	1.42	0.00	1.27	2.34	1.77	1.00	1.77	0.08
18b	6.50	6.50	6.50	1.71	144.28	61.52	1.60	38.45	2.50
19b	6.00	6.00	6.00	3.76	60.54	29.55	2.00	14.77	0.89
20b	10.71	9.29	3.57	5.54	27.34	7.70	1.88	4.11	0.44
21b	5.05	2.02	0.00	3.65	5.62	4.87	2.50	1.95	0.10
22b	2.88	0.00	0.00	3.36	1.95	1.37	1.00	1.37	0.04
23b	3.55	3.55	2.84	1.25	17.46	8.45	1.67	5.07	0.18
24b	2.02	2.02	1.01	2.13	9.49	9.49	2.00	4.74	0.10
25b	8.49	0.94	0.00	4.19	5.80	2.43	1.50	1.62	0.14
26b	11.11	8.33	0.69	1.21	17.82	5.66	2.29	2.48	0.28
27b	9.01	9.01	5.41	2.99	42.57	15.12	2.50	6.05	0.54
28b	6.76	2.70	0.00	2.50	9.16	3.48	2.00	1.74	0.12
29b	9.83	9.83	6.36	3.28	93.88	19.14	2.13	9.01	0.88
30b	6.38	6.38	0.00	1.27	8.65	8.65	3.00	2.88	0.18
31b	9.41	5.88	1.18	2.02	7.98	3.30	1.33	2.47	0.23
32b	1.27	1.27	1.27	2.59	4.85	4.85	1.00	4.85	0.06
33b	3.06	3.06	2.04	1.55	4.21	3.48	1.00	3.48	0.11
34b	1.06	0.00	0.00	0.51	1.31	1.31	1.00	1.31	0.01
35b	9.09	5.19	0.00	1.51	7.37	2.74	1.40	1.96	0.18
36b	6.25	3.75	0.00	1.53	4.81	3.70	1.67	2.22	0.14
37b	2.01	2.01	0.67	0.36	4.86	3.71	1.00	3.71	0.07
38b	4.67	3.74	0.00	3.43	5.18	2.94	1.25	2.36	0.11
39b	4.71	1.18	0.00	2.06	3.99	2.30	1.33	1.73	0.08
40b	11.34	11.34	11.34	5.99	114.70	34.69	2.75	12.62	1.43
41b	2.52	1.68	0.00	0.88	4.24	3.10	1.50	2.07	0.05
42b	14.52	12.10	4.03	6.24	16.99	6.30	1.80	3.50	0.51
43b	12.90	12.90	11.29	2.47	28.45	11.72	2.00	5.86	0.76
44b	8.22	2.74	1.37	1.42	4.30	2.26	1.00	2.26	0.19
45b	4.42	3.54	0.00	1.88	5.38	3.26	1.25	2.61	0.12

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