Multiparameter Prediction Model for Atrial Fibrillation after CABG

S Sovilj[1], G Rajsman[2], R Magjarevic[1]

[1]University of Zagreb, Faculty of Electrical Engineering and Computing, Zagreb, Croatia
[2]Clinical Hospital Center Zagreb, Department of Cardiac Surgery, Zagreb, Croatia

Abstract

The aim of the study was to develop a multiparameter prediction model of Atrial Fibrillation (AF) after Coronary Artery Bypass Grafting (CABG) based on measured P wave parameters. We recorded the standard II lead ECG for at least 48 hours after surgery in 48 patients. In contrast to previous research and in order to enable the analysis of more data we decided to record the ECG continuously. The ECGs were processed offline and a vector of 82 P-wave parameters was calculated for every hour of the record. The segmentation of the ECGs was based on wavelet QRS and P-wave detectors. The calculated P-wave parameters were used for building classification and regression trees. We built several decision trees (models) for discriminating the AF prone patients after CABG. With the best tree model, we were able to achieve specificity (96.55%), sensitivity (54,54%), positive predictivity (85.71%), negative predictivity (84.84 %), accuracy (85,00%).

1. Introduction

Atrial fibrillation (AF) is the most common postoperative complication occurring in 30–40% of patients after CABG. AF can affect patients health, cause hemodynamic changes, cerebral and other thromboembolisms, thus, demands antiarrhythmic or anticoagulant therapy. Patients developing post-operative AF usually do not have previous arrhythmic history [1].

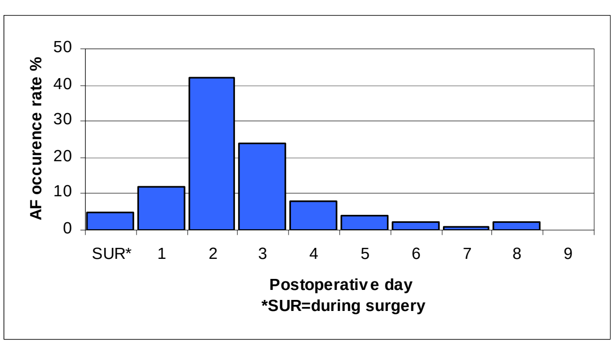

Figure 1. The occurrence rate histogram for AF.

Early risk detection of AF would contribute to prevention and enable forehand treatment with proper medications. An incidence of AF most frequently occurs on second or third day after CABG and optimal risk assessment needs to be done 24 hours before possible fibrillation appearance since prophylactic medication must be administered promptly.

2. Methods

Electrocardiograms were segmented with the QRS and P wave detectors based on wavelet transformation (WT) [2, 3]. Numerous P wave parameters were measured. The ECG acquisition from patients after CABG was obtained in collaboration with Clinical Hospital Center in Zagreb. ECG has been recorded from the standard surface II lead. Continuous recording lasted at least 48 hours after CABG. Sampling frequency has been 1000 Hz with amplitude resolution of 12 bits.

Parameters of the P wave from 48 patients' ECGs were statistically analyzed and those parameters which best discriminate the groups of patients with low risk and high risk of AF development were determined.

Classification model obtained from discriminant analysis and three models realized with classification trees are proposed.

Dyadic WT of signal was calculated based on the Mallat's algorithm. Mallat's algorithm presents the classic scheme better known as "two-channel subband coder". This algorithm is used for fast WT calculations which enable fast calculation of wavelet coefficients suitable for real time applications.

Local extremes on different wavelet scales are used for determining points of rapid change in the signal of electrocardiograms [3]. QRS complex produces the pair of a negative minimum and positive maximum in the wavelet transformation with the zero-crossing between them. This pair of extremes is often called modulus maxima. Zero-crossing of WT at all seven decomposition scales was used as the criteria for determining the R peak. The zero-crossing of the first wavelet scale 2^1 was used as a marker for R wave in ECG [4, 5].

The P waves were detected after the detection of R wave in a backward searching window, which precedes 200ms from the beginning of QRS complex, i.e. from the beginning of Q wave (Qonset). P wave can be detected by finding a pair module maxima The beginning of P wave matches the beginning and the end of this pair of extremes [5].

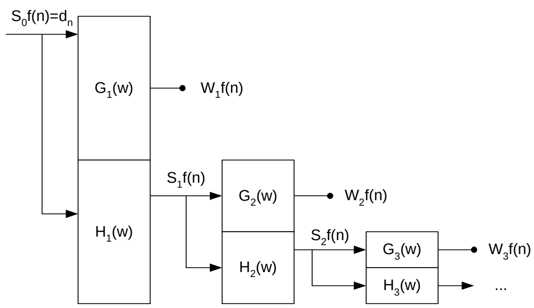

Figure 2. Realization of dyadic wavelet transformation like a filters bank towards Mallat's scheme.

P wave detection enables finding of five characteristic points: beginning (Ponset), peak (Ppeak) and end (Poffset), the point of the fastest rise (Pslope1) and the point of fastest fall (Pslope2) at all wavelet scales. The detected points are used for the calculation of different P wave parameters and their trends.

We tested our algorithm on all signals from MIT/BIH database. We found the sensitivity of 99.703 % and the positive predictivity of 99.726 % for our algorithm.

The probability distribution of the ECG parameters within one hour was considered normal distribution thus we calculated the mean value and standard deviation of every parameter for every hour of the patient ECG records.

The calculated parameters were divided in the following categories:

Time parameters:

1. P wave duration. Duration is measured as the difference between the P wave beginning (Ponset) and end (Poffset) at all wavelet scales. Longer duration of the P wave is related to the decrease in impulse velocity through the atrial tissue and is considered as an important parameter in the AF risk assessment.
2. Duration of PR interval. Duration is defined as the difference between the P wave peak (Ppeak) and the R wave peak (Rpeak).
3. Duration of PQ interval. Duration is defined as the difference between the P wave beginning (Ponset) and the Q wave beginning (Qonset).
4. Duration of the RR interval was used for the calculation of heart rate.
5. The values of Pslope1 and Pslope2 were calculated and they were proportional to the highest slope of rising P wave edge (Pslope1), and highest slope of falling P wave edge (Pslope2) respectively.
6. Time from Pslope1 and Pslope2
7. Absolute and relative P wave energy on different wavelet scales. Energy is calculated as the sum of squared wavelet coefficients inside the time interval from P wave onset to the P wave offset. The relative energy is calculated as the percent of content of every single wavelet scales in the total P wave energy.
8. Wavelet entropy. Wavelet entropy presents the measure of dispersion of P wave energy along different wavelet scales.

Other parameters:

9. Amplitude of P wave
10. Area below P wave

The software we developed enables the presentation of averaged P waves (every hour) synchronized with either P wave peak or R wave peak. It also makes possible to review all processed electrocardiograms with annotations produced by the detector (annotations of R peak, onset, peak and offset of P wave, etc.) and processing of new electrocardiograms. It is also possible to review trends of all measured P wave parameters and to display them in the state space.

3. Results

For the purpose of this study, electrocardiograms from 48 CABG patients were recorded from February 2004 to May 2006. The typical duration of the records was 48 hours of continuous recording per patient. For the statistical analysis of data the software package Statistica (Statistica 6, Statsoft, Inch., Tulsa, USA) was used.

Statistical analysis included 40 patients of which 11 (27.5 %) developed AF during or after the recording. 29 patients (72.5 %) did not develop AF neither during nor after the recording. For those patients who developed AF during the recording process, only that part of the record, which preceded the onset of AF, was included into the analysis.

We decided to exclude the ECG records of 8 patients because the detected number of R peaks in one hour was less than 2000 and/or the detected percentage of P waves was less than 75% compared to the number of detected R peaks.

For the records of the remaining 40 patients, we calculated 82 different parameters for every hour of the record.

Different P-wave and ECG parameters were analyzed and evaluated as possible indicators or predictors of AF using the independent t-test. Parameters with the level of significances $p<0.05$ were included into multivariate statistical analysis.

The group of patients which developed AF had significantly higher heart rate, shorter P wave duration and shorter PQ interval compared to the group of patients who did not develop AF.

The rise time and the fall time of the P wave are significantly larger in the group which did not develop AF. Absolute P wave energy on highest wavelet scale covering the part of ECG spectrum with predominant P wave spectral components appears larger in the group which did not develop AF, while the relative wavelet energy content does not show the statistical significance.

Classification and regression trees are usually built with C&RT algorithm (C&RT = classification and regression tree). Decision tree is a classification method that uses independent continuous and/or the nominal variables so that in every nod logical dividing (split) is performed depending upon the set criteria for best discrimination and classification in a particular class. In order to build the decision tree for discriminating the AF prone patients, we used those parameters, which are different for the two groups of patients for building a decision tree which could be used for monitoring the risk of AF development in patients after CABG.

A priori knowledge about the class size is also important data for building of decision trees and has influence on model prediction accuracy at the end of the process. We used the data from the literature which states that AF appears in approx. 30% of patients after CABG as a priori knowledge for our tree. We have tested several decision trees, i.e. changed weight factors in the algorithm for misclassification costs. In this paper, we describe the decision tree we called “model A”, which we found as the best in regard to the discrimination accuracy. The suggested classification tree Model A during its formation assumed equal cost for false classification for both classes.

The classification tree (Model A, Fig. 3) examines in the first nod the value of the parameter Pslope2AVR5 which is proportional to the slope of the falling edge of the P wave. If the value of this parameter is smaller than the threshold obtained by the C&RT algorithm (in this particular case set to 33.12), the case is classified as risky for AF development (the nod was marked with "yes "). If the value is larger than the set threshold, the next parameter (the heart rate - HeartRateAVR) is checked. If the value of the heart rate is smaller then 105.8 bpm, the case is classified as related in the group with a small risk to the AF development (the nod is marked with "no"). If the heart rate is larger than 105.8 bpm, another parameter has to be checked. In the Model A, the duration of PQ interval and a parameter proportional to the rise time of P wave rising edge (Pslope1AVR5) are used for decision making in the next nods.

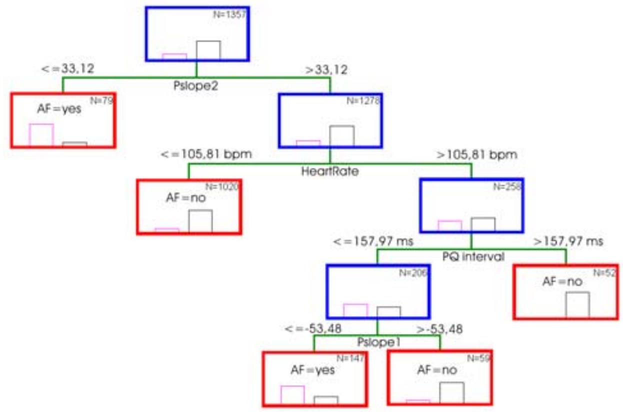

Figure 3. The classification tree (Model A).

Table 1. The classification tree (Model A).

Nod	Left	Right	Before nod	AF= "yes"	AF= "no"	Class	Measured parameter	Threshold
1	2	3	1357	333	1024	no	Pslope2AVR5	33,1
2			79	67	12	yes		
3	4	5	1278	266	1012	no	HeartRateAVR	105,8
4			1020	152	868	no		
5	32	33	258	114	144	no	PonQonAVR4	158,0
32	34	35	206	114	92	yes	Pslope1AVR5	-53,5
34			147	105	42	yes		
35			59	9	50	no		
33			52	0	52	no		

For the more reliable determining of AF risk for a particular patient, we suggested to use additional cumulative time criteria. This criterion binds the analyzed hours of ECG again and makes the decision related to a particular patient. This additional criterion actually monitors (counts) the hours in the ECG when the classification tree discriminated the ECG segment by showing risk parameters to developing AF.

Table 2. The classification matrix for the classification tree Model A. Columns of classification matrix present the number of the true and false prediction of Model A for every group, while rows present the number of true values in the used sample for every group, (true positive (TP), true negative (TN), false positive (FP) and false negative (FN).

	prediction «yes»	prediction «no»	total (hours)
true «yes»	TP 172	FN 161	333
true «no»	FP 54	TN 970	1024
total (hours)	226	1131	1357

Table 3. The classification matrix of Model A with

additional time criteria that counts if the number of risky hours is greater than 50 % of total number of currently recorded hours.

	prediction «yes»	*prediction «no»*	*total (patients)*
true «yes»	TP 6	FN 5	11
true «no»	FP 1	TN 28	29
total (patients)	7	33	40

Table 4. Working characteristics for Model A with additional time criteria.

Measure	*Definition*	*Value*
Sensitivity	$\frac{TP}{TP+FN}$	54,54 %
Specificity	$\frac{TN}{TN+FP}$	96,55 %
Positive predictivity	$\frac{TP}{TP+FP}$	85,71 %
Negative predictivity	$\frac{TN}{TN+FN}$	84,84 %
Accuracy	$\frac{TP+TN}{Total}$	85,00 %

4. Discussion and conclusions

The automatic P wave detection enables the measurement, processing and calculation of P wave parameters as well as continuous trend tracking of these parameters and their changes throughout the recording process. In this way it is possible to extract the number of clinically interesting and significant information. The use of the wavelet detector makes it possible to detect the QRS complex and the P wave with high accuracy and to measure numerous P wave related parameters.

The research of early detection of AF and other supraventricular arrhythmias is still in development and there is still no accepted diagnostic method or standardized procedure for the AF prediction. As possible predictors, some parameters of the ECG and/or the P wave in time and frequency domain, were considered [4, 6-7]. In all major studies, the ECG recording was only for a short period of time. Continuous recording and monitoring of the patients' ECGs after the surgery has not been used so far. In respect to the large number of data obtained by the long recording of ECGs we obtained from the group of 48 patients, and because of the difficulties in determining P wave parameters due to its small energy, we decided to analyze averaged ECG and averaged P wave parameters. The statistical analysis pointed out statistically significant parameters for differentiation of patient groups prone to AF development after CABG from those not prone.

The classification tree Model A is considered the best within the models we developed due to its high specificity and accuracy. P wave duration, as well as absolute and relative P wave energy on different wavelet scales, in contrast to our expectation and the results from the literature were not useful for discrimination between classes. For a more reliable determining of AF risk for a particular patient, we suggested to use additional cumulative time criteria. The suggested P-wave detection algorithm and the criteria based on classification tree "Model A" we introduced in this study, offers a possibility to use and process the ECG signal from the patient after CABG in real time and assess the risk of AF development.

Acknowledgements

This study was supported by Ministry of Science, Education and Sport of the Republic of Croatia under grant no. 0036007.

References

[1] Clavier L, Boucher JM, Lepage R, Blanc JJ, Cornily JC. Automatic P-wave analysis of patients prone to AF. Med Biol Eng Comput. 2002 Jan; 40(1):63-71.

[2] Sovilj S, Rajsman G, Magjarevic R. Continuous Multiparameter Monitoring of P Wave Parameters after CABG Using Wavelet Detector. Proc. Computers in Cardiology 2005; 32:945-8.

[3] Li C, Zheng C, Tai C. Detection of ECG characteristic points using wavelet transforms. IEEE Trans Biomed Eng. 1995 Jan; 42(1):21-8.

[4] Clavier L, Boucher JM, Blanc JJ. P-wave parameters for AF risk detection. Proceedings of the 18th annual international conference of the IEEE Engineering in Medicine and Biology society, 1996 Nov; 31(4):1367-8.

[5] Sovilj S., Jeras M., Magjarevic R. Real Time P-wave Detector Based on Wavelet Analysis. Proceedings of Melecon 2004, The 12th IEEE Mediterranean Electrotechnical Conference, 2004 May; (1):403-7.

[6] Guo Y, Hu S, Wu Q, Xu J, Song Y, Zhu X. Predictors of AF after coronary artery bypass graft surgery. Chin Med J (Engl). 2002 Feb; 115:232-4

[7] Poli S, Barbaro V, Bartolini P, Calcagnini G, Censi F. Prediction of AF from surface ECG: review of methods and algorithms. Ann 1st Super Sanita 2003; 39(2).

Address for correspondence

Sinisa Sovilj
Faculty of Electrical Engineering and Computing,
University of Zagreb
Unska 3, HR-10000 Zagreb, Croatia
sinisa.sovilj@ieee.org