

PRINCIPAL COMPONENT ANALYSIS OF THE P-WAVE

Quantification of Not-Dipolar Components of Atrial Depolarization

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Abstract: Aim of this study is to perform the principal component analysis (PCA) of the P-wave in patients prone to atrial fibrillation (AF). Eighteen patients affected by paroxysmal AF and implanted with dual chamber pacemakers were studied. Two 5-minute ECG recordings were performed: during spontaneous (SR) and paced rhythm (PR). ECG signals were acquired using a 32-lead mapping system (2048 Hz, 24 bit, 0-400 Hz bandwidth). For each patient, PCA of the averaged P-waves extracted in any of the 32 leads has been performed. We extracted PCA parameters related to the dipolar (using the first 3 PCs) and not dipolar (from the 4th to the 32nd PCs) components of the P-wave. The number of PCs according to the latent root criterion ranges between 2 and 3 during SR and between 2 and 4 during PR. PCA parameters related to the 3 largest PCs, and describing the dipolar component of the P-wave, did not significantly differ during SR and PR. The not dipolar components during SR were significantly lower than during PR (PCArEs%: 0.03±0.06 vs 0.12±0.21, p=0.001; PCArEs [mV⁴]: 0.10±0.14 vs 0.49±0.73, p=0.001). Factor analysis showed that on average all leads contributes to the first principal component.

1 INTRODUCTION

Atrial fibrillation (AF) is the most commonly encountered arrhythmia in clinical practice. It is defined by the absence of coordinated atrial systole, since it results from multiple reentrant electrical wavelets that move randomly around the atria. Although it is not a lethal disease, AF may increase mortality up to 2-fold, primarily due to embolic stroke.

Indeed, the lack of coordinated atrial contraction leads to unusual fluid flow states through the atrium that could favour the formation of thrombus at risk to embolize, especially after return to normal sinus rhythm.

The incidence of atrial fibrillation increases significantly with advancing age. When a patient spontaneously alternates between AF and a normal rhythm, the condition is known as paroxysmal AF.

When a patient continues with AF as the dominant cardiac rhythm without reversion to the normal rhythm, the condition is known as chronic AF. Two main electrophysiological conditions are indicated for AF initiation and perpetuation (Clavier et al., 2002): slower conduction velocity in some atrial areas and heterogeneity of cell refractory periods. This heterogeneity of structural and electrophysiological properties leads to a longer and more fragmented P-wave (Davies et al., 1963; Kawano et al., 1988; Dilaveris et al., 1998).

Thus, many studies focused on the analysis of the P-wave to extract parameters to recognize a patient with paroxysmal AF as well as to predict the development of AF (Dilaveris et al., 1998; Jordaeens et al., 1998; Dilaveris et al., 2001; Darbar et al., 2002; Dilaveris et al., 2002).

Given the technical difficulties to analyze the P-wave, and the different acquisition and processing

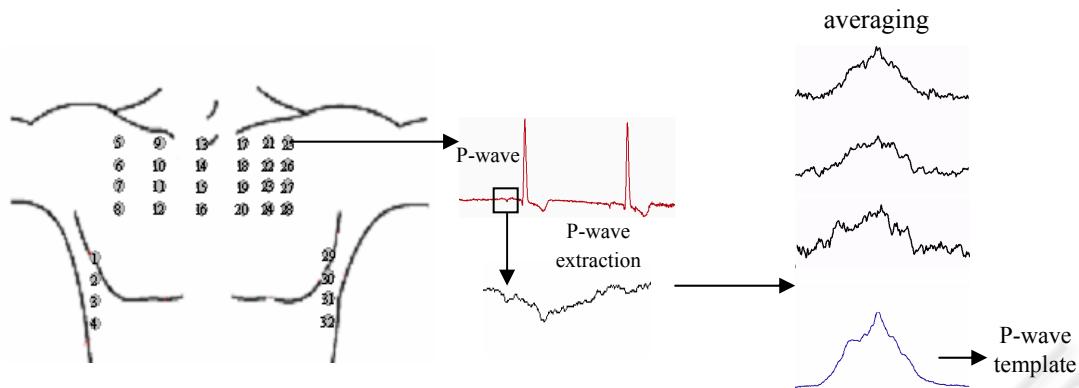


Figure 1: Scheme of the electrodes positioning and of the P-wave pre-processing procedure.

systems used, these studies often lead diverse and not-comparable results in terms of cutoff values. Indeed, the analysis of the T-wave, corresponding to the ventricular repolarization, has been extensively used to quantify repolarization inhomogeneity that may create an arrhythmogenic ventricular substrate. Promising results have been obtained by measuring the QT interval (QT dispersion) and by performing the principal component analysis of the T-wave (De Ambroggi et al., 1997; Acar et al, 1999; Malik et al., 2000; Kesek et al., 2004).

The former analysis have been already applied to the P-wave: P-wave dispersion (which is the difference between the maximum and the minimum P-wave duration recorded from the 12 standard leads), has been shown to distinguish patients with paroxysmal AF (Dilaveris et al., 1998; Jordaens et al., 1998; Dilaveris et al., 2001; Darbar et al., 2002; Dilaveris et al., 2002).

PCA of the T-wave has been extensively used to quantify both the complexity and the not dipolar components of the T-wave (De Ambroggi et al., 1997; Acar et al, 1999; Malik et al., 2000; Kesek et al., 2004); particularly, if the ECG would be completely explained by a single electrical dipole, the three largest principal components (PCs), and their corresponding orthogonal eigenvectors, would span the real three dimensional space (dipolar components), while the remaining PCs (not dipolar components) would be zero (Kesek et al., 2004).

For the T-wave it has been demonstrated that the not dipolar components, quantified by the PCA, are not zero, and reflect local repolarization inhomogeneity (Kesek et al., 2004). PCA has never been applied to the P-wave.

Following the approach already used for the analysis of the T-wave, the aim of this study is to perform the PCA of the P-wave in patients prone to

AF in order to: 1) evaluate how many principal components are necessary for an AF patient and in which way they are correlated with the ECG leads; 2) evaluate if and to which extent pacing affects the dipolar and the not dipolar components of the atrial depolarization (as quantified by PCA).

2 METHODS AND MATERIALS

2.1 Study Population

Nineteen patients with paroxysmal atrial fibrillation and permanent dual chamber pacemakers (AT500-Medtronic Inc., Minneapolis, MN, USA) were recruited from S. Filippo Neri Hospital, Rome, Italy. The AT500 device combines atrial sensing and detection algorithms for monitoring and diagnostics, and atrial therapy delivery functions. The system can store up to 35 episodes of atrial tachycardia/ flutter with electrograms and up to 128 episodes text summaries, without electrograms.

This pacemaker allows for accurate classification of atrial fibrillation episodes, with detailed information about episode instant of occurrence and duration, and further features three distinct programmable pacing algorithms that suppress atrial tachyarrhythmia trigger mechanisms.

When an episode occurs, the device is also programmed for arrhythmia termination. Three atrial pace-termination algorithms can recognise treatable atrial tachycardias and deliver antitachycardia pace-therapies to restore sinus rhythm.

The study population consisted of 9 female and 10 men, aged 72 ± 10 .

2.2 Experimental Protocols

Two five-minute recordings were performed for each subject. In the first recording the pacemaker was programmed in VVI mode, i.e. in single-chamber ventricular pacing mode set to a rate of 40/min, so that to have spontaneous rhythm.

In the second recording, pacemaker settings were changed back to the common operating DDD mode, i.e. with both atrial and ventricular pacing functions activated.

Recordings were made using a multi-lead mapping system for high-resolution biopotential measurement (ActiveTwo, Biosemi, The Netherlands).

The system is made of a battery powered isolated AD box that digitises the signals and transfers them to a PCI receiver on computer through a fibre-optic connection. The signals were digitised at a sampling rate of 2048 Hz and a resolution of 24 bits with a frequency response in the full DC-400Hz range.

No further filtering was applied to the data. Thirty-two leads were positioned on the thorax (figure 1), to allow accurate recordings of atrial signals.

ECG recordings were acquired as single-ended signals, with respect to a common reference position. Before starting the acquisition, signals were visualised on a computer screen to check for good electrode contact.

2.3 P-wave Pre-processing

Every lead signal was pre-processed and analysed to extract the average P-wave characteristic.

The first step is to isolate the P-waves from the acquired signals: after detecting the R-wave (using an algorithm similar to that proposed by Pan and Tompkins) (Pan and Tompkins, 1985), P-waves are extracted in a 200ms-long window (410 samples) starting 300ms before the R-wave (figure 1).

Secondly, a beat-by-beat linear piecewise interpolation was used to remove baseline wander, on each P-wave. Fiducial points for linear interpolation were taken from TP and PQ tracks of each beat.

Third, a P-wave template is constructed (figure 1) by averaging each extracted P-wave having a cross-correlation coefficient with the current template higher than 0.9.

In order to take into account the variations in PR interval and/or the inaccuracy in R-wave detection before averaging P-waves were aligned according to the lag at which the cross-correlation function

between the current averaged P-wave and each single P-wave shows its maximum (coherent averaging procedure).

The coherent averaging procedure went on until 200 beats were included. If the residual noise level (measured in the isoelectric TP track) remained at more than 1 μ V even after averaging of 200 beats, averaging procedure continued until the noise level reached a value lower than 1 μ V.

If it was impossible, the lead was excluded from the study.

2.4 Principal Component Analysis – Measures of Atrial Depolarizatrion Characteristics

For each patient, PCA of the 32 averaged P-waves extracted from the 32 leads has been performed. Since PCA transforms the measured P-wave to virtual parameters that are mutually independent (orthogonal), the 3 largest PCs would contain all the information in the P-wave stemming from the vectorial concept of a single electrical dipole. Following an approach already applied to the T-wave (Kesek et al., 2004; Acar et al, 1999), the other principal components (in this case from the 4th to the 32nd) represent the not dipolar components of the atrial depolarization.

We thus extracted the following parameters:

$$PCA_1 = \frac{s_1}{\sqrt{\sum_{i=2}^{32} s_i^2}} \times 100$$

$$PCA_2 = \frac{s_2}{s_1} \times 100$$

$$PCA_3 = \frac{s_3}{s_1} \times 100$$

$$PCArres = \sum_{i=4}^{32} s_i^2$$

$$PCArres\% = \frac{PCArres}{\sum_{i=1}^{32} s_i^2}$$

where s_i denotes the i -th eigenvalue associated with the i -th principal component. We also extracted the number of principal components suggested by the latent root criterion (PCA number).

In addition, in order to estimate to which extent each lead contributes to the first principal component, factor loadings have been calculated. Analogous to Pearson's coefficient, the squared

Table 1: Results of the PCA parameters during spontaneous rhythm (SR) and during paced rhythm (PR) for all 18 patients.

	PCA number		PCA1 [%]		PCA2 [%]		PCA3 [%]		PCAres [mV ⁴]		PCAres% [%]		
patient	SR	PR	SR	PR	SR	PR	SR	PR	SR	PR	SR	PR	
1	3	3	196.9	211.3	50.4	46.7	5.7	6.7	0.040	0.090	0.200	0.430	
2	2	3	917.6	288.0	10.8	34.0	1.4	6.6	0.001	0.020	0.006	0.120	
3	3	3	349.6	359.5	27.6	26.3	7.3	8.4	0.013	0.090	0.076	0.510	
4	2	3	634.4	401.0	15.6	23.9	1.8	6.6	0.014	0.040	0.104	0.240	
5	3	3	195.1	375.5	50.8	20.4	6.5	16.8	0.013	0.130	0.070	0.700	
6	3	2	114.2	716.62	84.5	3.4	23.1	1.8	0.010	0.020	0.040	0.100	
7	3	3	233.1	298.5	40.7	31.2	13.6	11.7	0.013	0.110	0.060	0.550	
8	2	2	231.3	187.0	38.2	53.2	20.2	5.4	0.014	0.006	0.069	0.026	
9	3	4	208.0	218.8	46.9	43.1	8.9	12.4	0.260	0.640	0.660	2.670	
10	2	2	883.2	277.6	11.3	35.9	0.9	2.6	0.001	0.043	0.004	0.230	
11	2	3	354.1	138.7	28.0	70.5	3.3	5.4	0.013	0.123	0.077	0.233	
12	3	2	588.0	159.2	15.9	62.8	6.0	2.1	0.001	0.002	0.063	0.008	
13	2	3	400.3	976.2	24.9	8.97	2.0	4.7	0.003	0.020	0.014	0.110	
14	3	2	850.9	132.3	10.8	75.5	4.6	3.1	0.004	0.001	0.022	0.006	
15	2	2	231.9	273.5	42.8	36.3	4.9	3.4	0.020	0.040	0.086	0.210	
16	2	4	356.4	849.1	21.9	11.7	17.4	1.4	0.015	0.010	0.065	0.050	
17	3	2	221.2	103.7	42.6	95.3	15.0	8.2	0.008	0.770	0.036	2.310	
18	3	2	313.3	115.7	30.8	86.2	8.3	5.1	0.024	0.090	0.130	0.340	
				404.4		337.9		33.0		42.5		8.4	
				257.5		247.3		18.3		25.9		6.5	
<i>p-value (Wilcoxon test)</i>		0.472		0.306		0.586		0.001		0.001			

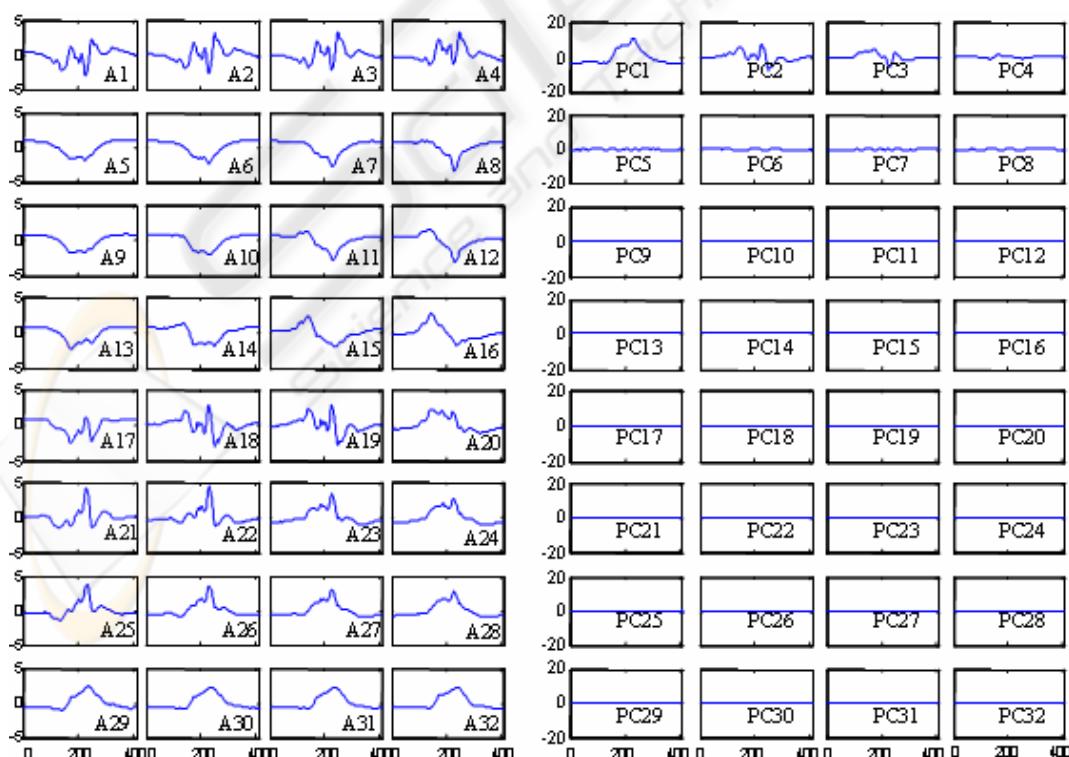


Figure 2: Example of the 32 P-wave templates and of the results of the PCA for one patient.

factor loading is the percent of variance in that variable explained by that PC (i.e the degree of correlation between the original data and the first principal component expressed in percentage).

In addition, in order to estimate to which extent each lead contributes to the first principal component, factor loadings have been calculated. Analogous to Pearson's coefficient, the squared factor loading is the percent of variance in that variable explained by that PC (i.e the degree of correlation between the original data and the first principal component expressed in percentage).

3 RESULTS

Figure 2 shows the 32 P-wave templates and the results of the PCA for one patient.

Table 1 summarizes the results obtained by the PCA parameters. The number of principal components according to the latent root criterion ranges between 2 and 3 ($2,56 \pm 0,51$) during spontaneous rhythm and between 2 and 4 during pacing ($2,67 \pm 0,69$, $p=0,6$).

PCA parameters related to the three largest PC (PCA₁[%], PCA₂[%] and PCA₃[%]), that describe the dipolar component of the P-wave, did not significantly differ during spontaneous and paced rhythm (table 1, Wilcoxon test for paired data). The not dipolar component (figure 3) as defined by both PCAres and PCAres% during spontaneous rhythm were significantly lower than during pacing (PCAres%: $0,03 \pm 0,06$ vs $0,12 \pm 0,21$, $p=0,001$; PCAres[mV⁴]: $0,10 \pm 0,14$ vs $0,49 \pm 0,73$, $p=0,001$).

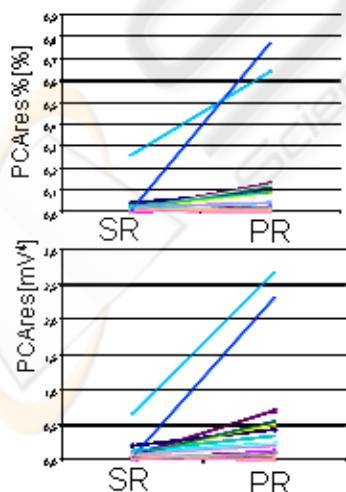


Figure 3: Notdipolar components as defined by both PCAres and PCAres% during spontaneous rhythm and during pacing.

Factor analysis showed that on average all leads contributes to the first principal components. Figure 4 shows the factor loadings averaged (in absolute values) all over the population during spontaneous rhythm and during pacing. Each lead but one in spontaneous rhythm (lead A17) correlates with the first principal component.

4 DISCUSSION

Analysis of the P-wave had been extensively developed to extract parameters related to atrial depolarization heterogeneities useful to recognize patients with paroxysmal AF or to predict the development and the perpetuation of AF (Dilaveris et al., 1998; Jordaens et al., 1998; Dilaveris et al., 2001; darbar et al., 2002; Dilaveris et al., 2002).

However, the technical difficulties to acquire and process the P-wave, had so far limited its clinical use. Indeed, promising results have been obtained by performing the PCA of the T-wave, in terms of quantification of ventricular repolarization inhomogeneity that may create an arrhythmogenic ventricular substrate (De Ambroggi et al., 1997; Acar et al, 1999; Malik et al., 2000; Kesek et al., 2004).

We hereby used an 32-lead ECG acquisition system particularly suitable for P-wave analysis, having 24 bit resolution and being DC-coupled. We performed the PCA of the P-wave in patients prone to AF. PCA has been applied to the average P-wave extracted in any of the 32 leads.

For each patient we extracted the same PCA parameters employed for the T-wave (Kesek et al., 2004; Acar et al, 1999). As for the T-wave, the PCA parameters related to the first three PCs are associated to the dipolar component of the P-wave, while the remaining PCs (form the 4th to the 32nd) are associated with the not dipolar component of the P-wave.

To our knowledge this is the first time the PCA is performed on the P-wave, thus physiological interpretation and critical discussion can be related only to previous experimental evidences of ventricular conduction disturbance (PCA of the T-wave) (Kesek et al., 2004; Acar et al, 1999).

The first important result is that pacing provokes a significant increase of the not dipolar components of the P-wave. Thus atrial pacing changes the atrial activation, disturbing the normal atrial depolarization process and generating additional paths not explainable by a single P-vector. Such a

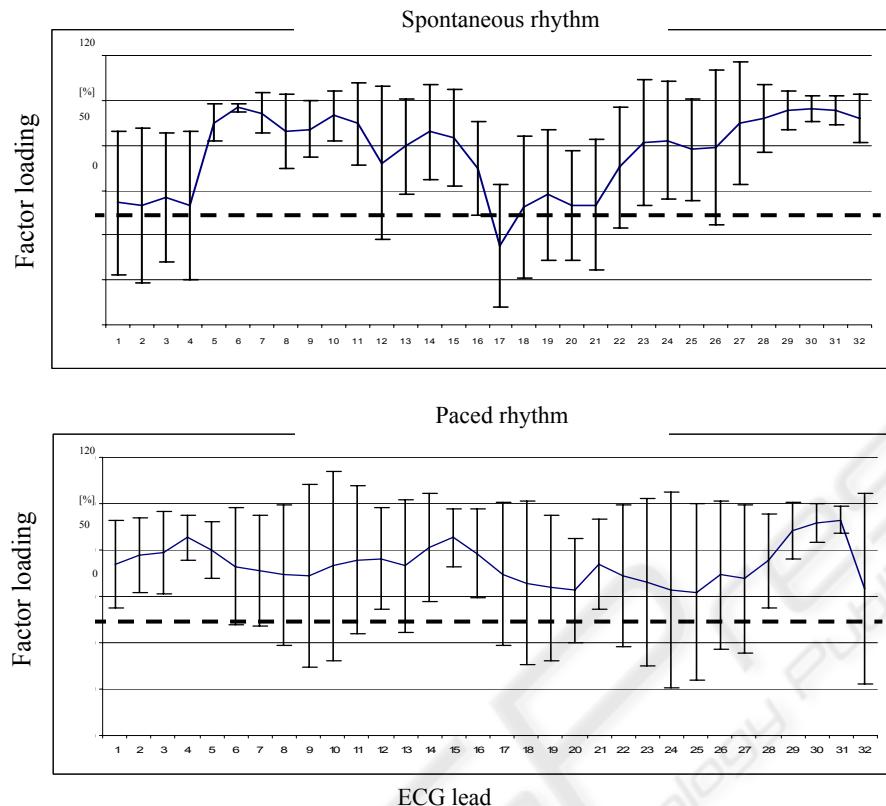


Figure 4: Factor loadings obtained during spontaneous rhythm and during pacing.

result is in agreement with previous studies showing an increase in P-wave duration and low-frequency energy during pacing respect to sinus rhythm in patients with AF (Keane et al., 1995). Non-dipolar components is plausible to be associated with local atrial depolarization inhomogeneity: pacing seems to provoke parts of the myocardium depolarized in a normal sequence and parts depolarized from an abnormal direction.

The second important results is that, on average, all the 32 leads contributes to the first PC, having a significant correlation coefficient with almost all variables.

Since any leads systematically show a not significant correlation with first PC, each lead seems to contribute to a similar extent to the dipolar component. However, we found an inter-patient variability for the factor loadings – some patients had not significant factor loadings in some leads. This result suggests that maps of the correlation with the first PC (or of the average correlation with the first 3 PCs) could help in identifying those leads (i.e. body surface zones) which mainly contribute to the dipolar component of the atrial depolarization. In conclusion, the study of the dipolar and not dipolar components of the P-wave could provide

important information not present in a classical ECG. If the assumption that the not dipolar signal is associated with local depolarization inhomogeneity of the atrium is correct, the PCA is a useful mathematic tool to deeply investigate the atrial conduction disturbances as well as the effects of pharmacological or electrical therapies. This first study tempting the PCA on the P-wave shows that pacing alters the atrial depolarization patterns, provoking an increase of the not dipolar component of the P-wave.

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