Long-Term Characterization of Arterial Blood Pressure Series

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Abstract

A simply method to study how arterial blood pressure values rise and fall during the till test, which is the tool universally used to evaluate people with faint episodes. Not only what is happening but how, that is calculating the angle and longitude of the arterial blood pressures ramps. This is accomplished from smoothed versions of the series of systolic pressure, which is approximated by line segments fitted to it. Then, the extracted features are used to make comparisons between the three groups; one group was formed with the controls. The other two groups include people with a history of syncope, which are classified as positive or negative depending on the results of tilt testing.

1. Introduction

Linear tendencies is the most intuitively method to study long term behaviour of a time series. The Autonomic Nervous Systems (ANS) modulates the heart rhythmic and vascular tone through the sympathetic and parasympathetic branches. For this reason several pathologies related to cardiac variables are analysed by means of the Heart Rate Variability (HRV)[1] which also involves other hemodynamics parameters, for example arterial blood pressure variability From continuous arterial pressure Diastolic Blood Pressure (DBP), Systolic Blood Pressure (SBP), and Mean Blood Pressure (MBP) time series can be obtained.

The variability of the cardiac parameters seems to be the result of the actions of several nonlinear control systems to adapt to different equilibrium conditions of the cardiovascular system. In this context, beat to beat changes are physiologically normal, but if it is supposed that ANS is in control, we can expect fluctuations around the equilibrium point of various cardiac parameters, including arterial blood pressure. This can be seen if we use a low-pass to eliminate fast variations and preserve the trend. If the ANS loses control we can expect a pressure drop with the consequent loss of consciousness, but without reaching this extreme, it is also important to study the performance of the ANS on people with faint precedents, that not reproduce syncope during the tilt test.

2. Methods and materials

2.1. Data acquisition

All of the records used in this study were registered from patients and healthy voluntaries at the Fernandez Hospital, during tilt test procedures. Records from patients with syncope precedents are classified as positives or negatives depending on the test results. Healthy subject's records are used as controls. Signal acquisition during tilt test includes electrocardiogram (ECG) and continuous blood pressure curve (CBPC), but other parameters as respiration and peripheric blood flow are sometimes also recorded. Sample rate on all the channels was 1200 samples/sec. Two signals are available as digital data for computer processing: beat to beat interval and beat to beat SBP and DBP. They are obtained respectively from ECG and CBPC.

2.2. Preprocessing

An automatic method for the detection of R wave on ECG [2] was applied to the data. A posterior manual editing of the marks of occurrence of the R waves is performed by experts. The intervals between R waves were used to form the RR event series. We used the information on the ECG channel to validate each beat in the arterial pressure channel. Another method [3] is used to detect fiducial points from continuous arterial blood pressure. This method was developed to be used in these studies were stationarity cannot be assured. Using these points the respective systolic, diastolic and pulse pressure series can be constructed.

2.3. The algorithm first stage filtering

The first stage that consist on getting a smoothed version of the point series, was implemented with a low-pass Butterworth zero phase filter of five order with a cut-off frequency of approximately 0.05 Hz. In the next figure you can visualize the result of applying this filter to a SBP series. The level of filtering is associated to the time of response of the ANS which is supposed to be similar to bandwidth of the filter used. Others algorithms have been tested to do this task, one based on wavelets and multiresolution analysis[4, 5], and the other named after Smooth Prior method[6]. The approach used is the one that brings the minor number of segments at the final stage.

2.4. Final stage detection and validation of breakpoints

The task now is to find breakpoints between straight lines which represent long term tendencies of the point series we are analyzing. The point of departure is the curve obtained as output of the filtering stage. The candidates to be breakpoints are the inflection points, but not all of them. We will only choose those which are between slopes of different sign. In mathematical words they have to be either maximums or minimums. An important fact is that, due to the low pass filtering there will be much less breakpoints. Checking the zero crossing of the gradient of the filter series we can select these breakpoints.

Each peak and valley is candidate to be a break-point. First of all, we compute the first derivative of the filtered point series. At the time of occurrence of a peak or valley the gradient changes sign and have a value towards zero. As only exists discrete values, the gradient will never equals zero, but we will start from the initial time and check for the sign of the gradient on successive points. To each change in the sign (zero cross) of the gradient of the filtered curve we can impose certain constraints to be accepted as a new breakpoints. If the constraints are overcome the time of occurrence of them will be save in a vector of breakpoints The constraints are optional, but they are not necessary as with other methods.

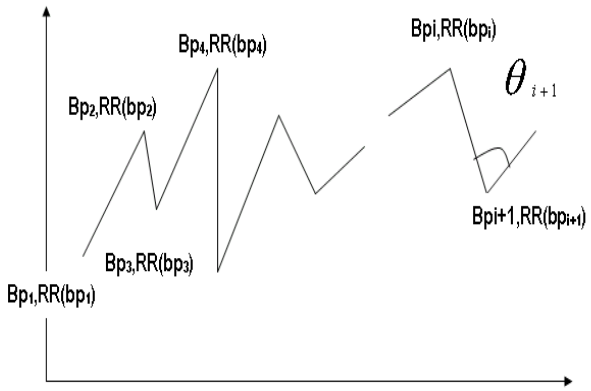

Figure 1. Linear segments and breakpoints.

To validate each breakpoint must fulfill two conditions

$\| Bp(m+1)-Bp(m) \| >$ Minimum length

$\| A(RRV(BP(m+1)/BP(m+1)) - A(RRV(BP(m)/BP(m)) \|$

>Minimum angle change (in radians)

Where A= Arc tang function.

Finally we will have a vector of validated breakpoints. We have saved the time of occurrence of the break-point, the other coordinate comes from replacing this time in the RRV series. It only rest to connect each break-point and obtain the tendencies

2.5. Application to SBP analysis

We use beat series of arterial systolic blood pressure from fifty subjects (33 females and 17 males). The files correspond to ten minutes of recording belonging to all of the groups (16 positives, 17 negatives, and 17 controls). As previously mentioned, the series are filtered to obtain a smoothed version of them. In Fig. 2 we can see a series corresponding to the group control plotted in blue color, and the filtered version superimposed in red color.

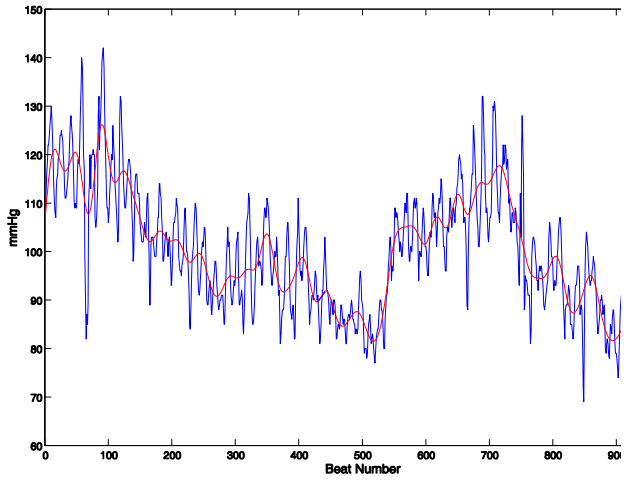

Figure 2. Arterial blood pressure series example from control group and the same series filtered superimposed in red.

Afterward this filter series is approximated by piecewise linear segments obtained as explained before. In Fig 3 we can observe the final stage. We have reduced the dimension of the problem from near one thousand to forty two breakpoints. Now it is much easier to study local characteristics on the evolution of these series.

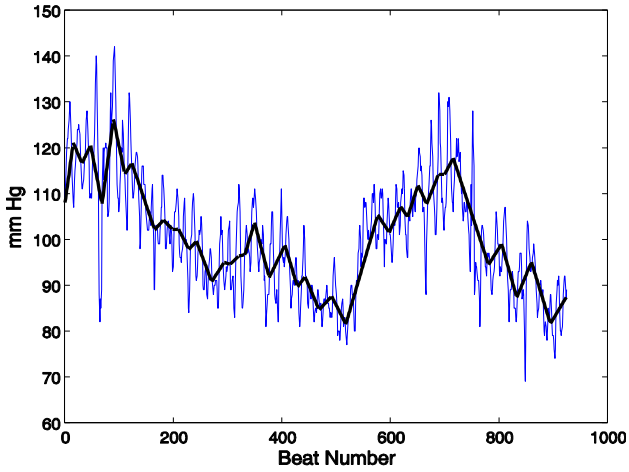

Figure 3. The same example shown in Fig.2 but now linear segments representation looks very similar to the smoothed version.

For example the length and angle of the slope of the ramps of pressure can be calculated for positive and negative increments of pressure, in a separated manner.

Of course it can also be calculated all together in a conventional manner.

The computations of positive and negative maxima of the mentioned parameters for each series are then used to look for features that are different among groups. These values for each group are analyzed using one way ANOVA.

3. Results

We have done a lot of trials and have not found significant statistically differences between the parameters, because means are similar, but all the results are consistent in the sense that there is an increment in blood pressure variability from controls to negatives and positives. In this case more variability in arterial blood pressure is not good and reveals that the subject is not healthy. More variability seems to be an indicator of less control of the pressure by means of ANS. That increment in the variability can be seen in the greater variances observed in negatives and positives with respect to controls. Table 1,2,3 summarizes the results.

Parameter	Positives	
	Mean	Variance
Systolic pressure (mmHg)	111,0788818	273,5683759
Mean pos. pressure ramps	5,505762525	4,982592541
Mean neg. pressure ramps	-6,54356576	6,603769487
Max. pos. pressure ramps	17,92972104	107,9188795
Max. neg. pressure ramps	-17,7076505	42,25733653
Max. angle at pos. ramps	30,43539831	140,1202178
Max. angle at neg. ramps	-31,5824521	132,3551665

Table 1. Mean and variance of parameters calculated for positives.

Parameter	Negatives	
	Mean	Variance
Systolic pressure (mmHg)	112,9132185	161,4094327
Mean pos. pressure ramps	6,264702754	11,33527795
Mean neg. pressure ramps	-6,04017231	10,97567651
Max. pos. pressure ramps	17,72708164	141,7506258
Max. neg. pressure ramps	-14,5730223	55,89688037
Max. angle at pos. ramps	32,58156925	232,2690252
Max. angle at neg. ramps	-30,4858373	197,6212626

Table 2. Mean and variance of parameters calculated for negatives.

Parameter	Controls	
	Mean	Variance
Systolic pressure (mmHg)	112,2140306	160,7694655
Mean pos. pressure ramps	5,348145664	3,97645478
Mean neg. pressure ramps	-5,29228000	4,713679334
Max. pos. pressure ramps	14,56316777	33,36496091
Max. neg. pressure ramps	-13,5336638	37,42933808
Max. angle at pos. ramps	27,51889266	117,83495
Max. angle at neg. ramps	-23,3676140	72,98493293

Table 3. Mean and variance of parameters calculated for controls.

Acknowledgments

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