Effect of Posture on the Cardiorespiratory System using Canonical Correlation Analysis

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Abstract

This research investigates the influence of body posture on cardiorespiratory regulation using canonical correlation analysis (CCA). Electrocardiogram (ECG) and blood pressure (BP) were recorded on 6 subjects in supine, sitting and standing position during 8 periods of 120 s. For each period, the tachogram, the systogram, the diastogram and an ECG-derived respiratory (EDR) signal were computed. CCA was applied to investigate the influence of the systogram, diastogram and respiration on the tachogram. The results show that a large amount of the variance in the tachogram can be explained by the influence of the systogram, diastogram and respiration (EDR) in standing position with respect to the other postures. It also shows an increased linear relationship between systolic BP and HR in standing position than in other postures. This relationship was in all cases positive, indicating that an increase in systolic BP results in a lower HR. Stronger linear RSA effects are present in sitting against supine position.

1. Introduction

In supine position all veins and arteries are more or less on the same level in the body. Therefore hydrostatic pressures will be distributed evenly throughout the body. In sitting and standing position on the other hand the blood will be pushed down towards the feet because of gravitational influences. Therefore, the pressure distribution in the body is dependent on the location one investigates: below the heart arterial and venous pressures will increase, while arterial and venous pressures will decrease above the heart [1]. Alterations in posture will be counteracted by the cardiovascular system and its regulatory mechanisms. One of these mechanisms is the baroreflex, which is the response of the body on changes in blood pressure (BP). An increase in mean arterial BP for example will decrease cardiac output and total peripheral resistance (TPR), hence counteracting BP changes [1]. Another regulation mechanism is Respiratory Sinus Arrhythmia (RSA), which is heart rate variability (HRV) in synchrony with respiration [2]. Exhalation will result in an increased RR-interval (RR-I) length and inhalation has the inverse effect. This is found to improve pulmonary gas circulation. RSA influences the Sinoatrial (SA) node by means of the parasympathetic branch of the autonomic nervous system. An increase in tidal volume will stimulate lung stretch receptors, which will cause an increase in heart rate (HR) and a decrease in TPR. This will partially cause RSA [1].

Canonical correlation analysis (CCA) can quantify the linear relationship between a set of independent and dependent variables and assess the level of dependency between the sets. In this research, CCA is used to investigate the baroreflex and RSA mechanisms, by means of studying the effect of BP and respiration on the HR.

2. Methods

2.1. Data aquisition

The data for this research originate from a larger study which aims at assessing the effect of weightlessness on the autonomic nervous system (ANS). In this research, the scope is limited to investigating postural effects during baseline measurements in normogravity. The test subjects that were selected were 6 healthy, non-smoking, male volunteers between 22 and 32 years of age (mean $\pm$ SD: 28$\pm$5 year) and free from any cardiovascular, metabolic or neural pathology (stature: 181$\pm$2cm; mass: 76$\pm$7kg; BMI: 23$\pm$2).

Data of each test subject were obtained in supine, sitting and standing position. The electrocardiogram (ECG) and arterial BP were continuously recorded during two periods of approximately 8 minutes for each posture. These measurements were segmented into epochs of 120 seconds, giving 8 datasets for each posture per test subject. Recording of the ECG and BP was done with the Nexfin monitor (BMEYE, Amsterdam, The Netherlands). The ECG was monitored with a lead II derivation at a sampling frequency of 1000 Hz. The arterial BP was measured non-invasively via photoplethysmography using a finger cuff wrapped around the middle finger. The finger pressure is representative for the arterial BP if the hand is held at heart level. The sampling frequency of the BP signal is 200 Hz.

2.2. Data pre-processing

From the ECG recordings, the tachogram was computed using R peak detection via the Pan-Tompkins algorithm [3]. To describe the variability of the blood pressure, two signals, the systogram and diastogram, were determined. The systogram consists of the subsequent systolic peaks from the continuous BP measurement, while the diastogram consists of its subsequent diastolic values. The systoles in the BP signal were detected with the template matching technique [4]. The diastoles were calculated as the minima in the BP in between subsequent systoles. A surrogate respiration (ECG-derived respiration or EDR) signal was acquired using the amplitude of succcessive R peaks with respect to the baseline, an EDR method which proved to be the best simple approximation of the respiratory signal [5].

Tachograms, systograms, diastograms and respiration (EDR) signals were resampled at 4 Hz using cubic spline interpolation.

2.3. Canonical correlation analysis

2.3.1. Methodology

CCA is a multivariate statistical model that makes it possible to determine if a set of dependent and a set of independent variables are related to each other and to what extent. CCA starts from a set of dependent variables X and a set of independent variables Y:

$$X = \begin{bmatrix} x_1(1) & \cdots & x_1(N) \\ \vdots & \cdots & \vdots \\ x_m(1) & \cdots & x_m(N) \end{bmatrix}, \quad (1)$$

$$Y = \begin{bmatrix} y_1(1) & \cdots & y_1(N) \\ \vdots & \cdots & \vdots \\ y_n(1) & \cdots & y_n(N) \end{bmatrix}, \quad (2)$$

where N is the number of samples, m is the number of variables in X and n is the number of variables in Y.

From each set a linear combination can be computed, which are called the canonical variates $\tilde{x}$ and $\tilde{y}$

$$\tilde{x} = w_x^T X, \quad (3)$$

$$\tilde{y} = w_y^T Y. \quad (4)$$

The relationship between two canonical variates is the canonical function. The regression coefficients of the corresponding canonical function are w_x^T and w_y^T are chosen such that the correlation between the resulting canonical variates is maximal. Therefore they are the results of the following maximization problem

$$\max \rho(w_x, w_y) = \frac{E((w_x^T X)(w_y^T Y))}{E((w_x^T X)(w_x^T X))E((w_y^T Y)(w_y^T Y))}. \quad (5)$$

The first canonical function is calculated so that the maximal correlation between the two sets of variables is described. The next canonical function describes the maximal correlation between the two sets that is not described in the previous canonical function and so on. Subsequently, canonical functions are mutually uncorrelated and the maximal number of canonical functions that can be extracted is equal to the number of variables in the smallest set [6].

It is important to notice that CCA is constrained to identifying linear relationships between the two sets of variables. Non-linear dynamics are thus not captured in the results.

2.3.2. Set determination

Respiration exerts an influence on the HRV, namely RSA [2]. It is also found that BP fluctuations are regulated through the baroreflex loop. An increased BP will result in a decreased HR, which corresponds with an increase in RR-I length [1]. From these mechanisms it can be concluded that the HR is dependent on changes in BP and respiration rate. Therefore, the tachogram was put in the dependent set and the systogram, diastogram and respiration (EDR) in the independent set. With this choice of sets, CCA measures of one canonical function were computed.

2.3.3. Interpreting the measures

The measures that can be computed with CCA and that are useful for further interpretation are the correlation coefficient, canonical loading of a variable and canonical cross-loading of a variable [6].

- Correlation coefficient: i.e. Pearson product-moment correlation coefficient between the canonical variates of the dependent and the independent set of variables. It is thus a measure of the size of the linear dependency between the two linear combinations.
- Canonical loading of a variable: i.e. the linear correlation between that variable and the own canonical variate. It is thus a measure that describes the influence of each variable to the own canonical variate; the larger the coefficient,

the higher its influence will be in deriving the canonical variate.

• Canonical cross-lading of a variable: i.e. the linear correlation between that variable and the canonical variate of the opposite set. With this measure the relationship between each variable and the other set can be represented, making it very useful for interpretational causes.

2.3.4. Significance testing

Before the measures of a CCA can be interpreted, their significances need to be tested. This is done by calculating three significance measures, namely the level of significance, the magnitude of the canonical relationship and the redundancy indices [6].

1. Level of significance: this is tested with the F-statistic in which the test has an F-distribution under the null hypothesis. In this case, it is used to test whether the CCA fits the population from which the data were sampled [7]. The results of one CCA are said to be significant if it satisfies the test with a 95% interval range (0.05 level). This corresponds to an F-value of minimally 3.68.
2. Magnitude of the canonical relationship: this is the squared correlation between two canonical variates and thus represents the shared variance between these variates.
3. Redundancy index: this is the amount of shared variance that can be explained by each canonical function. In a first step, the amount of shared variance between the canonical variates is computed. In the second step, a measure for the amount of variance in a canonical variate that can be explained by the opposite canonical variate is computed. This is done by taking the average of all the squared canonical loadings of one set. Finally, the redundancy index is the multiplication of both components.

Results of 132 CCA's were computed, 44 for each posture. Each of these results was tested for significance. The CCA results that had a redundancy index of the dependent set lower than 20% and an F-statistic lower than 3.68 were removed. For each posture 30 CCA results remain.

2.3.5. Statistical tests

Normality of the significant CCA measures was tested with a Lilliefors test. A box cox transformation was used on not-normal measures before applying one-way ANOVA [7]. The box cox transformation holds rank, but transforms the data as such that it will be distributed normally. One-way ANOVA was used to test for differences between postures.

When one-way ANOVA gave p-value smaller than the significance level ($\alpha = 0.05$), at least one of the groups was significantly different from the others. The Tukey-honestly significant difference (HSD) post-hoc test was used to look for significant differences between all postures if needed.

3. Results and discussion

Postural effects on the interactions of the physiological signals were examined by comparing the CCA results of measurements done on test subjects in different body positions. The results are shown in Tab. 1 as the median value plus or minus the distance to the upper or lower quartile.

There was an increasing trend in the correlation coefficient, going from supine to standing position, with significant differences among each posture. The amount of variance in the tachogram that can be explained by the independent canonical variate was thus higher in standing position compared to the other postures.

For the systogram, the canonical loadings showed an increasing trend going from supine to standing position, but only the canonical loading of the standing position was significantly different from the two others. The same was true for the canonical loadings of the diastogram; these went from negatively correlated with the own canonical variates to positively correlated, when body position went from supine to standing. Again, only the differences for the standing position with both other body positions were significant. The respiration canonical loadings were all negative and seemed to increase in absolute magnitude when going from supine to standing position. However, only the difference between supine and sitting position was significant.

An increasing trend was seen in the canonical cross-loadings of the systogram and diastogram, but only the cross-loading for the standing position was significantly different from the other postures. For the systogram the median canonical cross-loading was for all body positions positive, meaning that an increase in systolic BP will result in an increased RR-I length, corresponding with a decreased HR. This linear correlation becomes significantly stronger when the relationship was measured in standing position. This relationship is in correspondence with the baroreflex feed-back loop, which says that an increase in systolic BP will in time result in a decrease in HR and vice versa. A similar trend is true for the canonical cross-loading of the diastogram. However, this median value was negative in supine, around zero for sitting and positive for standing position. Therefore the interaction between the diastogram and tachogram will be dependent on body position; the canonical cross-loading in standing position was higher than those found in supine and sitting position. In the case of supine position, an increase in HR corresponded with an increase in diastolic BP, while in the case of standing position the opposite is true.

The cross-loadings of respiration (EDR) were all negative, showing an increasing trend in absolute value going from supine to sitting position. The values were significantly different for these two body positions. An inhalation will thus decrease the RR-I length and correspondingly in-

Table 1. CCA measures for different postures

CCA measures	*Supine*		*Sitting*		*Standing*	
Correlation coefficient						
First can. fun.	$0.58^{+0.05}_{-0.05}$	b,c	$0.59^{+0.06}_{-0.07}$	a,c	$0.73^{+0.06}_{-0.07}$	a,b
Canonical loadings - Independent set						
Systogram	$0.15^{+0.68}_{-0.33}$	c	$0.37^{+0.55}_{-0.31}$	c	$0.69^{+0.15}_{-0.16}$	a,b
Diastogram	$-0.46^{+0.23}_{-0.54}$	c	$-0.10^{+0.52}_{-0.34}$	c	$0.23^{+0.14}_{-0.43}$	a,b
Respiration	$-0.08^{+0.56}_{-0.39}$	b	$-0.58^{+0.28}_{-0.52}$	a	$-0.40^{+0.18}_{-0.41}$	
Canonical cross-loadings - Independent set						
Systogram	$0.09^{+0.40}_{-0.20}$	c	$0.23^{+0.31}_{-0.16}$	c	$0.52^{+0.10}_{-0.10}$	a,b
Diastogram	$-0.26^{+0.15}_{-0.31}$	c	$-0.05^{+0.27}_{-0.22}$	c	$0.17^{+0.09}_{-0.33}$	a,b
Respiration	$-0.06^{+0.28}_{-0.25}$	b	$-0.38^{+0.17}_{-0.34}$	a	$-0.31^{+0.12}_{-0.32}$	
$\text{median}^{\text{upper quartile}}_{\text{lower quartile}}$						
a: $p < 0.05$ vs. supine; b: $p < 0.05$ vs. sitting; c: $p < 0.05$ vs. standing						

crease the HR, while an exhalation will do the opposite. These findings correspond with the RSA theory. Furthermore, this relationship between tachogram and respiration (EDR) was more linear in sitting with respect to supine position.

4. Conclusion

CCA was applied to investigate the effect of posture on the baroreflex and RSA mechanism. It was found that a larger amount of the variance in the tachogram could be explained by the influence of the BP signals and respiration (EDR) in standing position compared to the other postures. Application of CCA also showed an increased linear relationship between systolic BP and HR in standing position than in other postures and stronger linear RSA effects in sitting against supine position.

Non-linear dynamics cannot be investigated with CCA, which is its most important disadvantage. On the other hand, multiple interactions of different physiological signals can be analyzed all at once. Therefore CCA is an appropriate method suited for the investigation of linear regulation mechanisms in the cardiorespiratory system

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