PRINCIPAL COMPONENT ANALYSIS OF CARDIOVASCULAR SYSTEM DYNAMICS IN HORSES

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Abstract: The paper deals with looking for significant phenomena contributing to increase of a risk of sudden cardiovascular death in well-trained horses during anaesthesia and/or contributes to reveal of fundamental control mechanisms that handle with some protection reactions of cardiovascular system during surgery.

Introduction

Mortality of horses under a total anaesthesia is still relatively high in spite of all the progress in a field of veterinary anesthesiology. According to the most extensive and the most complex study done in 6255 horses [Johnston GM et al., 1995] under anaesthesia the sudden death rate is around 0.9%. 39% of the deaths were caused by a failure of cardiovascular system.

Former research showed that monitoring of ordinary vital parameters as electrocardiography, pulse oxymetry, direct monitoring of blood pressure, gas concentration in respiratory system, state of the acidobasic equilibrium is not always able to reveal oncoming collapse of the cardiovascular system. However, our clinical experiences show that there is some relation between fitness condition of the horses and predisposition to the sudden cardiovascular death (surprisingly the greater risk for well trained horses). If we want to verify or exclude such a hypothesis, we have to analyze signals which primary characterize dynamics of cardiovascular system of horses under anaesthesia.

A lack of our previous research is the fact that the cardiovascular control models result from analysis of data measured under standard living conditions. It means that these models cannot be used for data measured during anaesthesia because it is not possible to influence activity and reactions of the cardiovascular system independently on the surgery. That is why, it is necessary to use different techniques that enable continual evaluation of the measured signals and their mutual relationships. Since the measured data do not carry only the useful but also some additional information it is usually necessary to remove the useless components and reveal more informative or new components.

Materials and Methods

ECG, CO_2 saturation, blood pressure signals that describe an activity of a cardiorespiratory system were recorded from horses by means of Datex-Ohmeda S/5TM monitor during anaesthesia and surgery.

The signals describe cardiovascular system activity and its control, electro-mechanical activity of heart and the activity of respiratory system. We assume that the signals can carry an information explaining causes of sudden cardiovascular death.

We assume that besides important information the recorded data contain some redundant useless information. The principal component analysis method (PCA) is one of the ways which can reveal these unimportant signal components and simplify the mutual relationships in the analyzed processes.

The basic principle of solution is introduced in Figure 1.

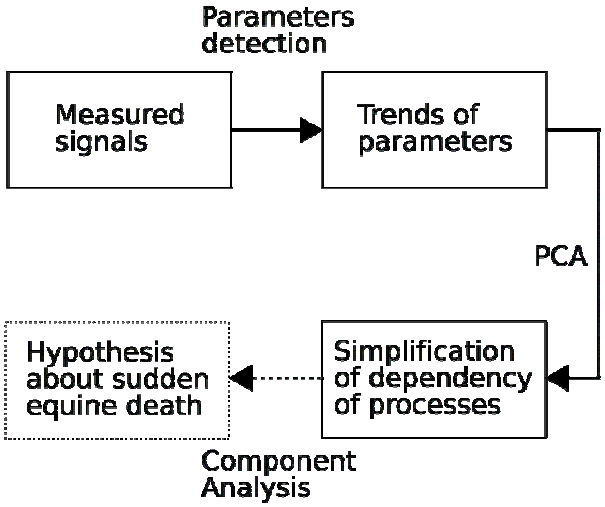

Figure 1: Block diagram of a project solution.

The principle of the PCA [1] [2] is in a transformation of an original p-dimensional space (in our case the p represents a number of the monitored signal parameters) into a new p-dimensional orthogonal space. It represents calculation of eigenvalues and

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eigenvectors of a covariation matrix **S** of input data. The input data are arranged in matrix **X**(n,p) where n represents number of observations of the p variables.

The k-th principal component Y_k of observation in matrix **X** is a linear combination

$$Y_k = v_{1k}X_1 + v_{2k}X_2 + \ldots + v_{pk}X_p = \mathbf{v}_k\mathbf{x}; \quad k = 1 \ldots p \tag{1}$$

of the variables which have maximum dispersion

$$s^2_{Y_k} = \mathbf{v}_k^T \mathbf{S} \mathbf{v}_k . \tag{2}$$

The coefficients v_{ik} of the linear combination described by eq. (1) are elements of the eigenvector v_k of the matrix **S** and the eigenvector corresponds to the k-th highest eigenvalue of the matrix **S**.

Results

Length of monitored signals recorded from horses corresponds to duration of surgery that takes hours. The signals usually contain non-removable artifacts and that is why signals from about 15 minute intervals were used for the analysis. The signals are sampled in order to use a maximum capacity of the monitoring system and with respect to their frequency spectrum: 300Hz for ECG signal; 100Hz for blood pressure signal; 25Hz for all other signals.

The seven parameters determined from the measured signals used for the PCA analysis are:

- interval between the R wave and the moment of the systolic blood pressure – x_1.
- diastolic blood pressure (the lowest value of blood pressure before systole) – x_2;
- heart rate determined from ECG signal (based on interval between two successive R waves) - x_3;
- heart rate determined from blood pressure signal (based on interval between two successive systoles) – x_4;
- mean blood pressure (mean value between two systoles) – x_5;
- minimal blood pressure (the lowest value of blood pressure. between two systoles) – x_6;
- systolic blood pressure (the highest value of blood pressure. in one heart period) – x_7;

The next figures and tables demonstrate some characteristic results.

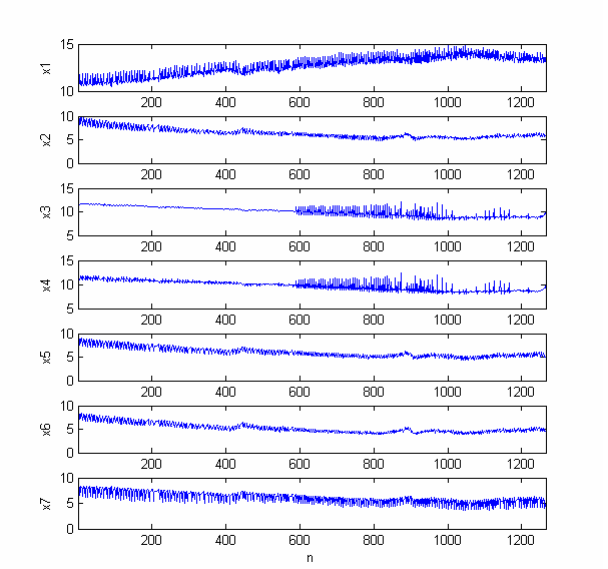

Figure 2: *Patient A – input signals normalized to standard deviation.*

Table 1: Patient A – computed principal component vectors.

	V1	v2	v3	v4	v5	v6	v7
x1	0.39	0.07	-0.35	0.81	0.23	-0.00	0.11
x2	-0.39	-0.25	-0.33	-0.09	0.70	0.20	-0.38
x3	-0.36	0.59	-0.14	0.13	-0.23	0.66	-0.01
x4	-0.36	0.61	0.07	0.08	0.26	-0.65	0.01
x5	-0.39	-0.25	-0.10	0.02	0.11	0.03	0.87
x6	-0.38	-0.27	-0.52	0.18	-0.57	-0.31	-0.23
x7	-0.37	-0.28	0.68	0.53	-0.03	0.07	-0.18

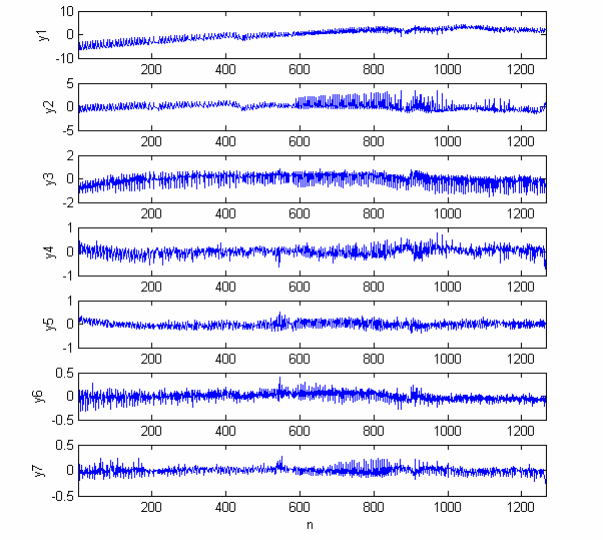

Figure 3: *Patient A – principal components curves.*

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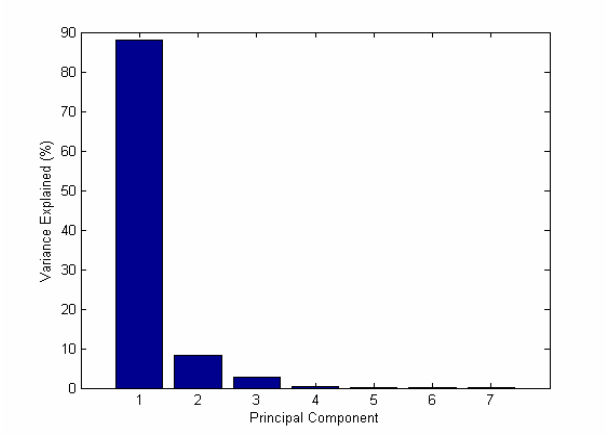

Figure 4: *Patient A – percent variability explained by each principal component.*

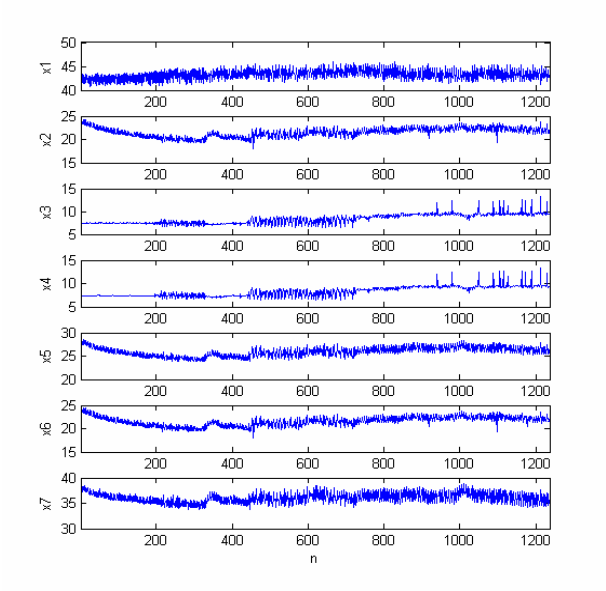

Figure 5: *Patient B – input signals normalized to standard deviation.*

Table 2: Patient B – computed principal component vectors.

	v1	v2	v3	v4	v5	v6	v7
X1	0.17	0.64	0.60	0.46	-0.01	0.02	0.03
X2	-0.44	-0.05	0.39	-0.27	0.28	-0.60	0.37
X3	-0.35	0.49	-0.38	-0.00	0.08	-0.36	-0.60
X4	-0.35	0.46	-0.40	-0.05	0.02	0.37	0.61
X5	-0.45	-0.10	0.18	0.06	-0.87	-0.00	-0.04
X6	-0.44	-0.06	0.38	-0.25	0.32	0.61	-0.36
X7	-0.37	-0.36	-0.13	0.81	0.26	-0.00	0.04

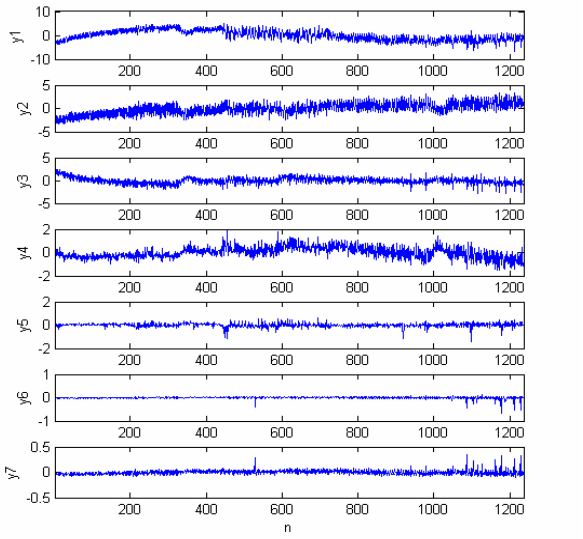

Figure 6: *Patient B – principal components curves.*

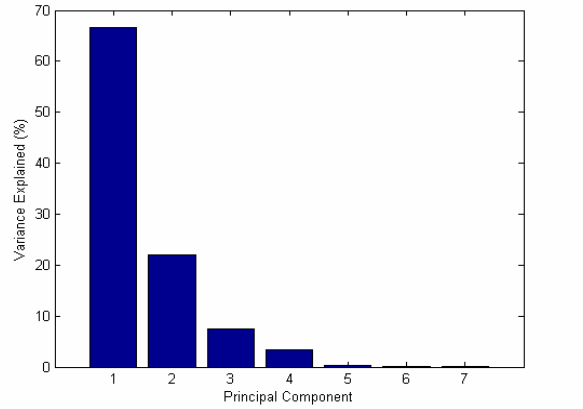

Figure 7: *Patient B – percent variability explained by each principal component.*

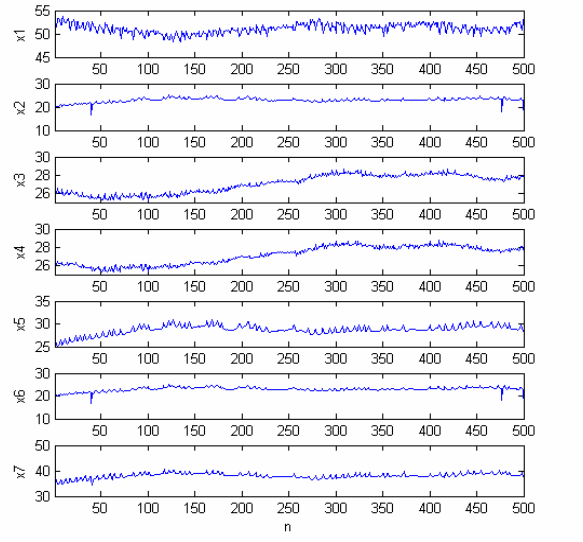

Figure 8**:** *Patient C – input signals normalized to standard deviation.*

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Table 3: Patient C – computed principal component vectors.

	v1	v2	v3	v4	v5	v6	v7
x1	-0.36	0.37	0.48	0.70	0.14	-0.07	0.00
x2	0.46	0.05	0.50	-0.15	0.11	-0.01	-0.71
x3	0.06	0.65	-0.18	-0.13	0.08	0.72	0.00
x4	0.07	0.65	-0.21	-0.23	-0.03	-0.69	0.00
x5	0.48	0.07	-0.14	0.46	-0.73	0.03	0.00
x6	0.46	0.05	0.50	-0.15	0.11	-0.01	-0.71
x7	0.46	-0.08	-0.43	0.43	0.64	-0.07	0.00

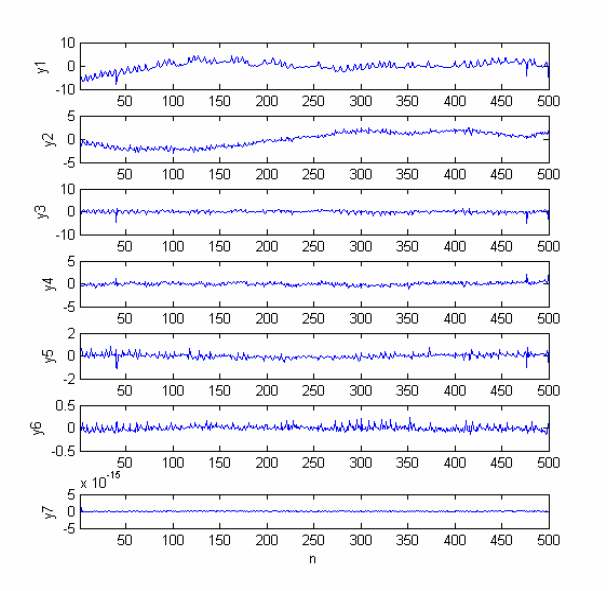

Figure 9: *Patient C – principal components curves.*

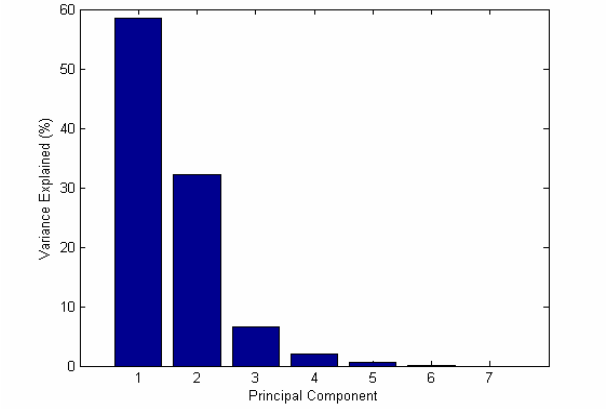

Figure 10: *Patient C – percent variability explained by each principal component.*

Discussion

The obtained PCA results for all the patients can be divided into three categories according to the eigenvector properties and variances of the particular principal components.

Fig. 2., Fig. 5. and Fig. 8 show PCA input data from the mentioned three particular categories that were determined from the measured signals.

The obtained and described PCA results mean that we can be interested in the first three principal components only, because thay contain over 95% of the total variability of the original signal parameters.

The first category is characterized by a great variability of the first principal component (over 88%) and relatively balanced composition of the particular parameters as it is apparent from the similar values in the first column in the Tab. 1. and from Fig. 4. It also means relatively strong linear dependency between the input parameters of PCA. We can consider that there is only one control mechanism behind all the parameters.

The second category has considerable part of total variability also in other components (Fig. 7.) but there is relatively balanced composition of the parameters again (Tab. 2.). It is difficult to say which of the parameters is the more informative.

The third category is the most interesting from all of our results because the information is distributed into more components (Fig. 10.) and the values of the eigenvectors components usually differ in order (Tab. 3.).

In the 2nd and 3rd category we can consider two or more mechanisms that control the behavior of particular parameters.

Conclusion

The advantage of PCA is relatively low time consumption for a calculation and that is why PCA seems to be suitable to reach further goals connected with the implementation of the complete analysis into the system for the real-time prediction of emergency situations during surgery of horses.

Our results will be compared to detailed clinical information about the examined horses and to results from another algorithm like independent component analysis (ICA) to confirm mentioned three categories.

Acknowledgement

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