Non-invasive Arterial Pressure Signal Estimation from Electrocardiographic Signals

J.C. Silva[1], J.S. de Oliveira[1], S.E. Silva[1], M.H. de Carvalho[1] and A.S. Silveira[2]

[1] Faculty of Electrical and Biomedical Engineering, Federal University of Pará, Belém, Brazil
[2] Laboratory of Control and Systems, Federal University of Pará, Belém, Brazil

Abstract— **In this paper, it is proposed an arterial pressure signal estimation technique from electrocardiographic signals. The study also covers, fundamentally, applying knowledge from the biomedical engineering field, in analysis and signal processing of biomedical signals, because it makes use of digital filters, correlation, covariance and other methods of signal treatment, using developing tools to assist medical diagnostics. The implemented method is based on the Kalman filter's use, which was designed considering a system model obtained from invasive arterial pressure measurements to allow the development of a non-invasive technique. Obtained results granted the estimation of the systolic and diastolic pressures, to ensure this fact, the study took into account the analysis of the system's performance by evaluating the quantitative mean of the estimation error, the RMSE index.**

Keywords— **Arterial pressure estimation, ECG, Kalman filter, RMSE.**

I. INTRODUCTION

The human body has several integrated systems that can and should be measured. The more reliable the measurement, the better. One of these systems is the cardiovascular, in which some important related measurements are: Heart Rate (HR), Double Product (DP) and Blood Pressure (BP) [1].

HR, as cardiac monitors developed, has been monitored with significant precision, but BP does not have a method that is, at the same time, effective, safe, and practical. There are currently four methods: one invasive direct and three non-invasive indirect methods [1].

Direct measurement is done by a catheter inserted into an artery, which is connected to a transducer which continuously and accurately sends the BP information. It is an accurate, however impractical method if it is necessary to investigate the BP behavior before, during, and after a physical exercise. Furthermore, the literature cites bleeding risks, pain, and invaded partial artery occlusion [1].

The other three indirect methods are: through a device called finapres that uses plethysmography, the traditional auscultatory method using the sphygmomanometer apparatus and the oscillometric method, which is used by automatic and semi-automatic devices. Each of them has its advantages and disadvantages [1].

Similarly to direct methods, the Finapres is fixed to the middle finger of the hand using a pneumatic adjustment and continuously measures BP. It brings all the advantages of direct plus the absence of discomfort caused by the pain and bleeding risks. However, in the same way as other direct methods, it prevents the analysis during exercise activities and other which requires the free mobility of the upper limb where the device is attached [2].

The traditional auscultatory, with an inflatable clamp, despite mobility limitations and discontinuity of measurements, is still the most viable and used. However, a factor that may present different measures is the difficulty of perceiving knockoff noises that determine the systolic and diastolic value; the accuracy depends on the auditory evaluator sensitivity [3].

In the oscillometric method, the device determines by oscillometry the maximum oscillation point, which corresponds to the mean blood pressure [3]. However, the BP responses during exercise activities and other everyday tasks which require the free mobility of individuals are still controversial, and more studies are necessary to ensure the accuracy of the BP measurement in these situations, and with this, the patient safety and the correct data interpretation [4].

Thus, developing an BP signal estimation system from the fusion of the BP dynamical model and the electrocardiographic signal (ECG) data by Kalman filter (KF) aims to access such important information for efficient patient monitoring. ECG is an examination that measures the heart electrical activity. Thus, this study explains the possibility of extracting systolic and diastolic pressure values through the ECG and how it relates to BP dynamical model using the KF to estimate the blood pressure [5].

The Kalman filter choice as the main element to achieve success in this research came from the fact that it can be applied via recursive algorithm, which can be performed in real time [6], in this case from the data obtained by ECG.

For a better understanding of the research, an analogy is made of the functioning of the FK with the human body. In which, the ECG sensors, which correspond to the FK state equation, have the objective of estimating what is happening inside the body, which corresponds to the FK output equations.

In this process, no matter how accurate the equipment is, there are errors due to measurement noises and uncertainties in the relationship between the internal and external sides, these errors are part of what one wants to filter, and the state variables involved in the problem allow access to the desired information. Through this methodology, it is proposed to estimate blood pressure without causing considerable discomfort to the patient.

II. MATERIALS AND METHODS

With the Kalman filter, it is possible to estimate the state of a system as follows: the filter receives the signal measured by a sensor, with uncertainties and noise, and performs a comparison based on the current estimated state and its expectation of the output estimated by its dynamic model, and with this, makes the next state prospection. For this purpose, it is considered that the model is defined in the state space. This model is described through state and output equations, where the output is the measured part, and the state can only be partially measured, requiring the use of an estimator such as the KF for its complete determination [7].

A. Signal processing

In this study, the database used was taken from the Massachusetts General Hospital / Marquette Foundation (MGH / MF) Waveform Database available on the Physionet.org website [8]. The database consists of electronic recordings from stable and unstable patients in critical care units, which it includes three ECG leads (I, II and V2), arterial pressure, pulmonary arterial pressure, central venous pressure, respiratory impedance, and airway CO2 waveforms. However, in this study, only ECG and blood pressure data were used. The data were recorded on 8-channel instrument tape with an effective sampling rate of 360 Hz and digitized at 12-bit resolution.The data file mgh002.mat was selected and edited, separating the data between the 815 to 821 seconds of the recording.

With the aim of identifying and removing artifacts that are commonly encountered in biomedical signals [9], an analysis was performed in the frequency-domain (Fig. 1), by applying the fast Fourier transform using the SCILAB software to detect high and Low-frequency artifacts, and base-line drift in the ECG signals. Considering the bandwidth of interest of the ECG signal is 0.05 up to 100 Hz [9], a high-pass filter with a cut-off frequency of 3 Hz was applied to remove base-line drift.

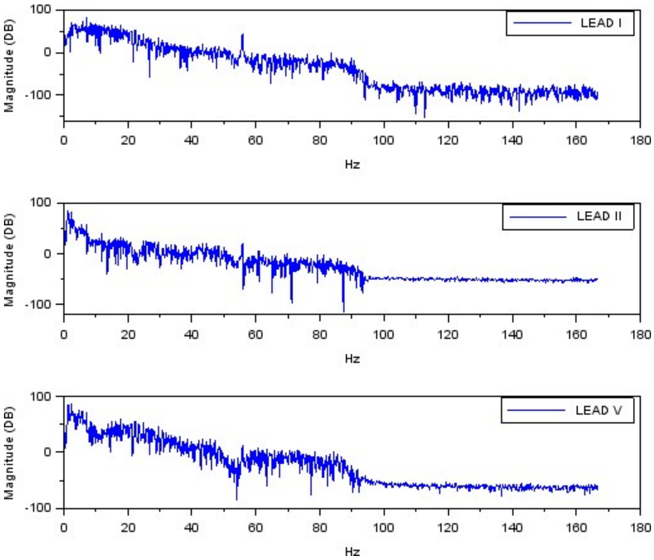

Fig. 1: Fast Fourier transform of the ECG signals

In order to consider the modeling of a dynamic system that relates pressure data with ECG data, is was evaluated the degree of correlation between blood pressure and ECG data represented by Leads I, II, V2. Both the filtered ECG signals and the original signals were analyzed based on the Pearson correlation coefficient matrix.

B. Kalman filter

The Kalman filter aims to minimize the quadratic error in the estimation of the states of a dynamic system corrupted by Gaussian noise [6, 10]. Such a dynamic system represents, for example, existing processes in the human body.

A generalized state-space representation of a stochastic dynamic system, with discrete time and time-varying parameters, has the following form:

$$x(k+1) = A(k)x(k) + B(k)u(k) + w(k) \quad (1)$$

$$y(k) = C(k)x(k) + v(k) \quad (2)$$

In Eq. (1), the matrices $A(k)$ and $B(k)$ are, respectively, the dynamic and input matrices, $x(k)$ is the state vector, $u(k)$ is the input vector and $w(k)$ is the process noise, Gaussian, i.e., zero mean with covariance matrix $Q(k)$. In Eq. (2), $C(k)$ is the output matrix, $y(k)$ is the measured output vector and $v(k)$ is the Gaussian measurement noise whose covariance matrix is $R(k)$.

The Kalman filter is an estimator system that is based on the state observer structure based on equations (1) and (2). It is a system that operates in closed loop, feeding back the measured output and, simultaneously, comparing it with the estimated output. This estimator has the following form:

$$\hat{x}(k+1) = A(k)\hat{x}(k) + B(k)u(k) + L(k)\left[y(k) - \hat{y}(k)\right] \quad (3)$$

$$\hat{y}(k) = C(k)\hat{x}(k) \quad (4)$$

where $\hat{x}(k)$ and $\hat{y}(k)$ are the estimated state vector and the estimated output vector, respectively.

The design problem requires knowledge of the matrices of the dynamic system and the covariance matrices of the Gaussian noises in order to determine the optimal gain $L(k)$ that minimizes the state estimation error, i.e., $\tilde{x}(k) = x(k) - \hat{x}(k)$. The recursive algorithm to determine the optimal gain is based, respectively, on the iterative solution of the Riccati difference equation and the gain calculation is given by [6]:

$$\begin{aligned} S(i+1) &= Q(k) + A(k)S(i)A^T(k) \\ &- A(k)C^T(k)\left(C(k)S(i)C^T(k) + R(k)\right)^{-1} C(k)S(i)A^T(k) \end{aligned} \quad (5)$$

$$L(k) = A(k)S(i+1)C^T(k)\left[C^T(k)S(i+1)C^T(k) + R(k)\right]^{-1} \quad (6)$$

For the design of the Kalman filter to be feasible, the realization of the system in the state space must be observable.

The recursive solution can implement the adaptive case ($i = k$) and can also be used for the design of the Kalman filter in steady-state [6], i.e., $S(i \to \infty)$, for when the system matrices are time-invariant. This method was adopted in this work because the model of the system is obtained from measured blood pressure data, but which will not be available during the next pressure estimation phase. Thus, it is not possible to adapt the matrices $A(k)$, $B(k)$, $C(k)$, $Q(k)$, $R(k)$, in real-time. In this way, parametric modeling and estimation are performed offline, generating a discrete and time-invariant model based on Eqs. (1) and (2).

C. System modeling

In the method proposed for this study, the data were separated into training and validation data. In the training phase, the parameters of the biomedical system model in the state space – Matrix A, Eq. (1) – were identified using the least-squares method (LS), which consists on minimizing the sum of the squares of the difference between the real and estimated values [11].

It was considered a state-space model with five state variables, $x_1(k), \ldots, x_5(k)$, corresponding to Lead I, Lead II, Lead V2, BP and BP Speed (vBP), considering that ART is an available measurement in this phase. However, in the validation phase, the available BP measurements served only to analyze how the estimated blood pressure fits with respect to the real data.

The problem treated consists only of the state and output variables, having no inputs and assuming that the parameters are invariant over time. Under these conditions, equations (1) and (2) are rewritten in the following forms:

$$x(k+1) = Ax(k) + w(k) \quad (7)$$

$$y(k) = Cx(k) + v(k) \quad (8)$$

where the state vector is described by

$$x(k) = \begin{bmatrix} x_1(k) & x_2(k) & x_3(k) & x_4(k) & x_5(k) \end{bmatrix}^T \quad (9)$$

In this study, to identify the system using LS, it is necessary to determine the parameters matrix and the regressors matrix, Θ and Φ, respectively.

The matrix of regressors has its lines constituted based on the vectors of regressors, in such a way that for N records of the observed state variables $\mathbf{X^T} = \begin{bmatrix} x^T(0) & \cdots & x^T(N) \end{bmatrix}$, the matrix assumes the following form:

$$\Phi = \begin{bmatrix} x_1(k-1) & \cdots & x_5(k-1) \\ & \vdots & \\ x_1(k-N) & \cdots & x_5(k-N) \end{bmatrix} \quad (10)$$

The estimated parameters matrix is given by:

$$\Theta = \left(\Phi^T \Phi\right)^{-1} \Phi^T \mathbf{X} \quad (11)$$

Through the transposition of Θ it is possible to obtain the A matrix of the model. Therefore, to estimate the blood pressure using the Kalman filter, the C matrix was redefined to

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad (12)$$

since only the variables of the electrocardiographic signals are considered measured variables, and the pressure signal and its speed are estimated.

If the covariance matrix of the LS estimation error, $\left(\Phi^T \Phi\right)^{-1}$, is invertible and the state-space realization is observable, then the Kalman filter can be applied for state estimation.

D. Estimation performance analysis

To obtain a quantitative measure of the estimation error, the differences between the real values and the estimated ones were assessed using the root mean squared error (RMSE) [5]. The RMSE is calculated according to the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} |y(i) - \hat{y}(i)|^2}{N}} \tag{13}$$

where $y(i)$, $\hat{y}(i)$ and N are the measured value, the estimated value, and the number of samples, respectively. In addition to the RMSE index, the variance of the signals was also analyzed. The variance quantifies the degree of dispersion of a variable in relation to its average value. It was calculated according to the following equation [6]:

$$Var(\bar{e}) = \frac{1}{N}\sum_{i=1}^{N}[\bar{e}(i) - \mu_e]^2 \tag{14}$$

where $\bar{e}(i) = y(i) - \hat{y}(i)$ and $\mu_{\bar{e}}$ is the average of $\bar{e}$.

For the RMSE and variance indices, the lower their values the better the estimated values fit the real data.

III. Results

The coefficient matrix for the analysis based on the filtered signals is shown in Table 1 and on the original signals in Table 2.

Table 1: Pearson correlation coefficient matrix (ECG filtered)

	Lead I	Lead II	Lead V2	BP
Lead I	1	0.2218398	0.2397051	0.0724656
Lead II	0.2218398	1	-0.5991580	0.1240340
Lead V2	0.2397051	- 0.5991580	1	0.0674538
BP	0.0724656	0.1240340	-0.0674538	1

Table 2: Pearson correlation coefficient matrix (ECG original)

	Lead I	Lead II	Lead V2	BP
Lead I	1	0.2215837	0.1446745	0.2053429
Lead II	0.2215837	1	- 0.7452250	0.7028911
Lead V2	0.1446745	-0.7452250	1	- 0.4715354
BP	0.2053429	0.7028911	-0.4715354	1

The correlation of some of the Leads with BP, before filtering, reached up to 70%, while with filtered data, a maximum of 12% was observed. Therefore, the data chosen to estimate a dynamic model in the state space that correlates blood pressure and ECG signals was the unfiltered one.

Figure 2 shows the result of the blood pressure estimate that is very far from the real one, since the beginning of the real pressure is close to 100 mmHg and the estimated one is close to 0 mmHg.

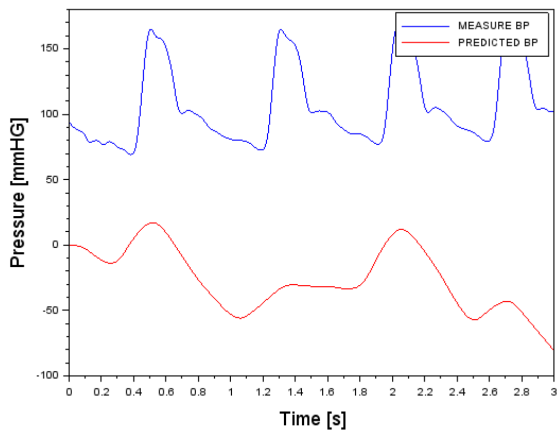

Fig. 2: Comparison between measured BP and predicted BP

For a better blood pressure estimation, using pre-filtering concepts , in which the offset is removed [9], a change was made to the baseline of the BP measurements. Thus, at the end of the estimation, the mean value which have been initially removed was added to the signal so that the systolic blood pressure (SBP) and diastolic blood pressure (DBP) values were within the real values in mmHG (Fig. 3).

Table 3 was constructed in order to asses the quality of the estimation in terms of the RMSE and variance performance indices, where it is possible to verify a significant improvement of such indices after the baseline adjustment.

Table 3: Estimation performance indices

	RMSE	Variance
No baseline adjustment	136.38	1083.05
With baseline adjustment	24.509	599.72

IV. Discussion

The BP estimation system, based on ECG signals, allowed a reliable estimation taking into account the presented comparison with the measured BP signal. The proposed method intends to highlight the relationship between ECG and BP. It can also be stated that this system had an acceptable performance considering that the result of the estimation is close to SBP and DBP values recorded on medical devices used

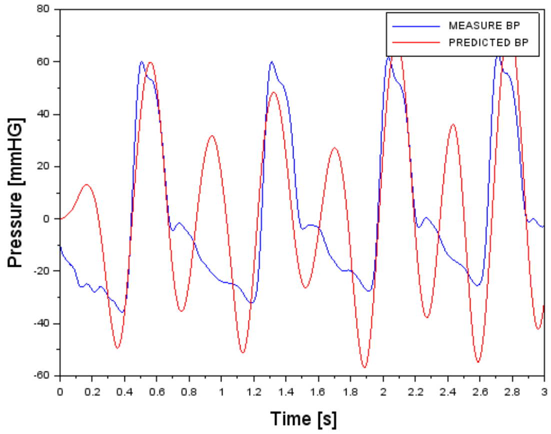

Fig. 3: Comparison between measured BP and predicted BP after the baseline correction

in critical care units. Thus, it is expected that this algorithm could improve real-time and non-invasive BP estimation in currently available devices, under development or in future systems.

The values obtained in the estimation were similar to SBP and DBP measurements, as shown in Figure 3, while the intermediate value was very far from expected. However, given that when we talk about blood pressure measurement, the values used in practice are systolic and diastolic pressures, the methodology is valid.

Although the variance was high, the RMSE was considered satisfactory when compared to already published values such as in [5]. Instead of evaluating the whole signal, if just SBP and DBP values were considered, after appropriate signal processing of both measured and predicted data, it might be possible to observe an increased performance based on our presented technique.

The Kalman filter provides an estimate of the blood pressure with good accuracy and robustness to disturbances. Although the data used are from patients in intensive care units, it is possible to notice that, even in this situation, there is a correlation between blood pressure and the electrical signals of the heart, allowing an estimation. The results' performance of the algorithm are comparable to various methods developed in this field, as is the case of a similar work that was published in the journal Sensors [5].

It is important to point out that the great contribution of estimation in state space, especially in the optimal case established with the Kalman filter, is that it is based on a multiple input and multiple output approach, using a very well established concept, for example, in estimators used in aerospace navigation systems, by fusing sensors and that the benefits can be summed up as follows: "you always gain by adding a new sensor in terms of reducing the estimation error, no matter how bad the additional measure is " [12]. In this study, BP showed around 20.5%, 70.5% and 47.1% correlation with the ECG channels Lead I, Lead II and Lead V2, respectively, and in the fusion with the Kalman filter, even though Lead I and Lead V2 have less correlation with BP (eg, "no matter how bad the additional measure is"), these three channels together contribute to reduce the BP estimation error.

Lastly, It was possible to verify that the removal of the low-frequency content, in this investigated case, has decreased the correlation of the ECG signals and the blood pressure. That is, part of the correlated dynamics lies in the low frequencies of the ECG signal.

V. Conclusion

This study has shown a real and objective application of dynamical systems identification and Kalman filtering within the area of Biomedical Engineering. These signal processing and analysis techniques are promising in the study of biological systems, proposing improvements in patient measurement and monitoring techniques using sensors. This algorithm is expected to improve blood pressure measurement devices currently available, in development or in future systems. Finally, it is worth noting that the study proved to be promising, validating one signal's estimates based on the values of another, it can be optimized about the system's identification to reduce the RMSE and variance indices. Future research can verify whether such changes could be achieved by using more data and more ECG leads to model the system, considering that the data used in this study were limited.

Conflict of Interest

The authors declare that they have no conflict of interest.

Acknowledgement

A. S. Silveira acknowledges the finantial support of the National Council for Scientific and Technological Development (CNPq, project 408559/2016-0).

References

1. Polito MD. Considerações sobre a medida da pressão arterial em exercícios contra resistência *Revista Brasileira de Medicina do Esporte, Vol. 9, nº 1.* 2003.

2. Medidas Contínuas da Pressão Arterial – Finapres NOVA at https://www.biolinkmedical.com.br/produto/pesquisa-em-hipertensao/monitor-de-pressao-arterial-continua/medidas-continuas-da-pressao-arterial-finapres-nova/
3. Quais as formas de se medir a pressão arterial? at https://cardiopapers.com.br/quais-as-formas-de-se-medir-a-pressao-arterial/
4. Scher LML, Ferriolli E, Moriguti JC, Lima NKC. Pressão Arterial Obtida pelos Métodos Oscilométrico e Auscultatório Antes e Após Exercício em Idosos Blood Pressure Assessed through Oscillometric and Aus *Arq. Bras. Cardiol. vol.94 no.5.* 2010:656–662.
5. Simjanoska M, *et al.* . Non-Invasive Blood Pressure Estimation from ECG Using Machine Learning Techniques *Sensors.* 2018.
6. Lewis FL, Xie L, Popa D. Optimal and Robust Estimation: with an introduction to stochastic control theory. 2nd Ed. CRC Press *Taylor & Francis Group.* 2008.
7. Greg W, Bishop G. An Introduction to the Kalman Filter *Department of Computer Science University of North Carolina.* 2006.
8. JP Welch, PJ Ford, RS Teplick, RM Rubsamen. Comprehensive collection of critical care waveforms. J Clinical Monitoring 7 *The Massachusetts General Hospital-Marquette Foundation Hemodynamic and Electrocardiographic Database.* 1991.
9. Rangayyan RM. *Biomedical Signal Analysis*. Canada: John Wiley Sons 2015.
10. Diniz PSR. *Adaptive Filtering: Algorithms an Practical Implementation - Fourth Edition*. Rio de Janeiro: Springer 2001.
11. Vicario F. OKID as a general approach to linear and bilinear system identification *Dissertação (Doutorado) - Columbia University.* 2014.
12. Kabamba PT, Girard AR. *Fundamentals of Aerospace Navigation and Guidance*. Cambridge, United Kingdom: Cambridge University Press, doi: 10.1017/CBO9781107741751 2014.