Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Effect of considering constant variance time-frequency autoregressive models for HRV analysis

Mercedes J. Gaitán-González, *Member, IEEE,* Salvador Carrasco-Sosa, Ramón González-Camarena, and Oscar Yanez-Suarez, *Member, IEEE*

***Abstract*—Time-varying autoregressive modeling may consider the driving noise variance as a constant. In this work, the properties of the autoregressive driving noise variance of heart rate variability, with different stationary physiological conditions (resting in supine and sitting; exercise) are obtained. The effect of constant variance consideration for ramp exercise and recovery (a nonstationary condition) is also evaluated by the comparison of the time-varying absolute spectral parameters obtained by parametric estimation, allowing or not the modeling of time-varying noise variance, and a non-parametric time-frequency analysis. The driving noise variance presented a direct non-linear relationship with the heart period for the stationary maneuvers (r=0.91), while for the nonsationary condition, the use of a constant driving noise resulted in bias for the estimation of heart rate variability spectral parameters. A time-varying driving noise variance should be considered.**

I. Introduction

The stationarity assumption is common in the assessment of heart rate variability under different physiological conditions [1]. The spectral analysis of stationary signals is done using either non-parametric or parametric estimators. In the parametric case, the use of autoregressive models is common. Several approaches are used to determine the model parameters, the autoregressive coefficients and the driving noise variance. Each time a heart period time series is modeled, the corresponding noise variance is estimated. Thus, if for the same individual several records are processed at different physiological conditions, each series would have its own estimated noise variance that may change on a record-by-record basis.

Several physiological conditions may produce nonstationary heart period time series, for example in maneuvers that do not reach a steady state, like the incremental exercise and early recovery. The evaluation of the autonomic nervous system out of steady state conditions is of interest [2-9]. These conditions require a different analytic approach. As in the stationary case, the tool may be nonparametric, using time-frequency representations as those from the Cohen class or time-scale as wavelets, or parametric, using a time-varying autoregressive model. In the latter, the autoregressive coefficients are allowed to change in time, while the driving noise variance is considered as a constant [2],

$$\begin{aligned} &\mathrm{RR}[n] = a_1[n]\mathrm{RR}[n-1] + \ldots + a_P[n]\mathrm{RR}[n-P] + \varepsilon[n] \\ &\varepsilon \sim \mathrm{WN}(0,\sigma^2) \end{aligned} \tag{1}$$

where $a_k[n]$ is the k-th autoregressive coefficient at time n, P is the model order, and σ^2 is the constant variance of the driving noise (ε).

Using this model, the temporal changes in the power spectral density are regarded to be only caused by varying pole positions with respect to the unit circle. In other words, under this approach for a dynamic maneuver, the changing autonomic modulation would be modeled based on the same driving noise input variance and only the autoregressive filter is considered to change, as can be observed in equation (2):

$$\mathrm{PSD}_{\mathrm{RR}}(\omega, n) = \frac{\sigma^2}{\left| 1 - a_1[n]e^{j\omega} + \ldots + a_P[P]e^{j\omega P} \right|^2} \tag{2}$$

This condition differs from the stationary approach where the driving noise variance is estimated for each particular signal, modeling the autonomic differences not only with different filters but also with different inputs to those filters.

The objective of this work was to evaluate the changes on the driving noise variance estimated in different maneuvers that result in stationary heart rate variability time series with different autonomic modulation, and to evaluate the effect of considering that variance as constant for a nonstationary case such as incremental exercise and recovery.

Manuscript received April 24th, 2006.

M. J. Gaitan-González is with the Departamento de Ciencias de la Salud, Universidad Autónoma Metropolitana Iztapalapa, México City, Mexico 09360 Mexico (corresponding author: 5255-5804-4734; fax: 5255-5804-4732; e-mail: mjgg@ xanum.uam.mx).

S. Carrasco-Sosa is with the Departamento de Ciencias de la Salud, Universidad Autónoma Metropolitana Iztapalapa, México City, Mexico 09360 Mexico (e-mail: scas@ xanum.uam.mx)

R. González-Camarena is with the Departamento de Ciencias de la Salud, Universidad Autónoma Metropolitana Iztapalapa, México City, Mexico 09360 Mexico (e-mail: rgc@ xanum.uam.mx)

O. Yánez-Suárez is with the Departamento de Ingeniería Eléctrica, Universidad Autónoma Metropolitana Iztapalapa, México City, Mexico 09360 Mexico (e-mail: yaso@ xanum.uam.mx)

II. METHODOLOGY

A. Subjects

Ten subjects, four women and six men, life-long residents of Mexico City participated in the study. Their anthropometric measurements expressed as mean ± standard deviation were: height 163.7 ± 8.3 cm and weight 61.3 ± 10.5 Kg. Subjects were healthy as established by clinical examination and electrocardiogram at rest, young (23.2 ± 1.8 years old), non-smokers, and sedentary. Their written informed consent was requested to participate. None of the subjects took any food, alcoholic or stimulant beverages, nor performed intense exercise 12 hours prior to the study.

B. Protocol

To establish the autoregressive driving noise variance dependence with the physiological condition, three five-minute stationary maneuvers were used: resting in supine and sitting positions, and exercise in a cycle ergometer (818E, Monark, Varberg, Sweden) at a load high enough to ensure a mean heart rate of 100 beats per minute. All recordings started once a steady state heart rate condition was achieved.

The nonstationary maneuver was dynamic ramp exercise and it consisted on successive one minute workloads of 0, 25, 50, 75 watt, followed by a three-minute recovery in sitting position (the subject remained seated on the ergometer) to complete a seven-minute maneuver. Between maneuvers, enough time was spent to allow the subject to recover.

In all cases, electrocardiogram was obtained using bipolar lead CM5 with a monitor (78330A Hewlett Packard, USA). The signal was digitized at a sampling frequency of 500Hz, using a 12 bit ADC converter and recorded for offline processing. None of the participants presented ectopic beats.

C. Preprocessing

The electrocardiogram was processed to detect the R wave peak occurrence; beat-by-beat heart period was obtained as the RR interval; it was interpolated and even sampled at 2.8 Hz by spline interpolation, and the trend was removed by means of the smoothness priors algorithm [10].

D. Signal processing

In the stationary case, the autoregressive models were estimated using the Levinson-Durbin algorithm. The model order was fixed to 15 and the goodness of fit was assessed for each time series. The driving noise was estimated as the prediction error. The mean heart period was obtained for the entire record.

For the nonstationary maneuver, the model was estimated using the recursive least squares algorithm for the same order as for the stationary case, and the noise variance was obtained from the whole prediction error (constant) and using a moving window of 25s (time-varying). Also, the Born-Jordan time-frequency distribution was computed. Time-varying low- and high-frequency heart rate variability components as well as the total power were computed by integration within the respective band for each time and each approach.

E. Statistical analysis

For the stationary case, driving noise variance was compared among the maneuvers using ANOVA for repeated measures. To assess the relationship between the noise variance and the autonomic tone evaluated as the heart period, a log-log regression was obtained between the driving noise variance estimator and the heart rate.

In order to evaluate the effect of using a constant noise variance, linear regression analysis was performed between the non-parametric and parametric cases for each spectral index and each subject. The correlation coefficients were compared by a paired t-test. In all cases, the significance level used was 0.05.

III. RESULTS

From the stationary time-series, the mean heart period presented significant differences among the maneuver ($p<0.01$). The estimated driving noise variance changed significantly between exercise and rest in both positions ($p<0.01$) with the highest variance for the supine position, and the lowest for exercise (Table I). Figure 1 shows the driving noise variance vs. heart period plot. A significant log-log direct relationship was obtained ($r = 0.91$, $p<0.01$).

TABLE I. MEAN ± STANDARD DEVIATION OF MEAN HEART PERIOD AND FINAL PREDICTION ERROR VARIANCE FOR THE STATIONARY MANEUVERS

	Supine position	Sitting position	Exercise
Heart period (ms)	956 ± 136	806 ± 82	406 ± 24
Noise variance (ms^2)	42.8 ± 24.1*	30.8 ± 25.1*	3.6 ± 2.3

All mean heart periods were different ($p<0.01$)
* significant differences with exercise $p<0.01$

The results for the nonstationary maneuver are presented in Table II. Correlation coefficients computed using the time-varying noise variance were significantly higher ($p<0.01$) for all spectral indexes. Figure 2 displays a typical example of the relationship between the total power obtained from parametric and non-parametric power spectral estimators; in general, those relationships were better when the noise variance was allowed to change using a sliding window to estimate its variance.

Bias was observed for the constant noise variance estimator, the low- and high-frequency components were higher than the non-parametric estimator for low-value components, while they were lower for high-amplitude components, as occurred with the total power (Figure 3).

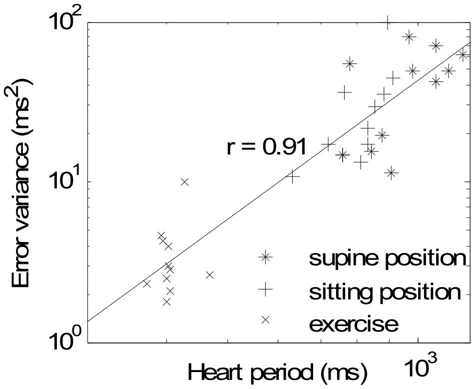

Figure 1. Log-log relationship between final prediction error variance and mean heart period for the stationary maneuvers.

TABLE II. CORRELATION COEFFICIENTS (MEAN ± STANDARD DEVIATION) BETWEEN PARAMETRIC AND NON-PARAMETRIC ESTIMATORS OF POWER SPECTRAL INDEXES FOR BOTH NOISE VARIANCE APROACHES.

	Total Power	Low-frequency	High-frequency
Time-varying noise variance	0.80±0.06	0.75±0.08	0.74±0.11
Constant noise variance	0.59±0.19	0.61±0.16	0.53±0.17

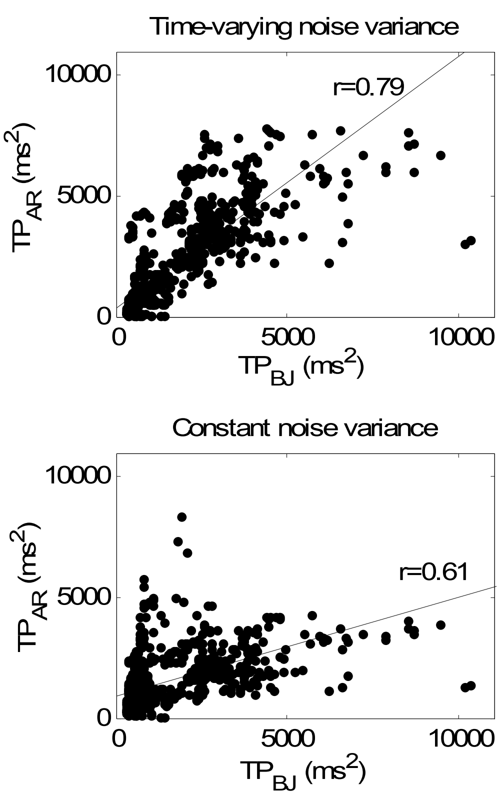

Figure 2. Typical example of the total power spectral values obtained by parametric (TP_{AR}) and non-parametric estimators (TP_{BJ}) for the time-varying (top) and constant (bottom) noise variance approaches.

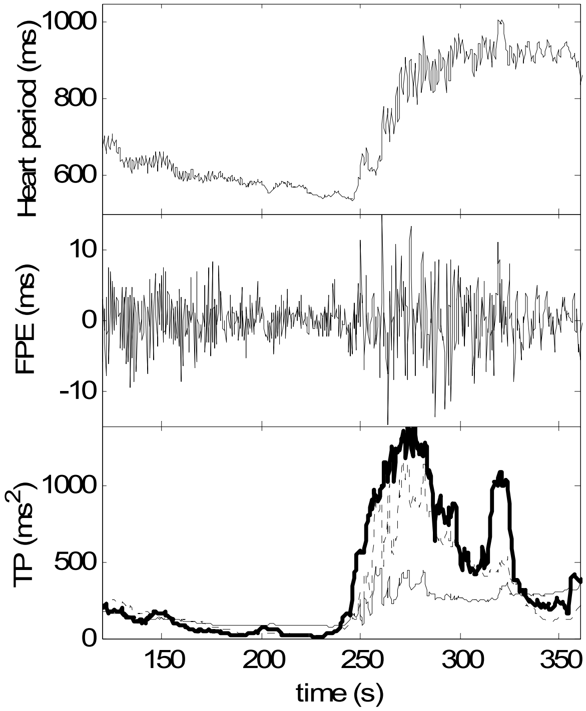

Figure 3. Example of the last two minutes of exercise and the first one of recovery a) heart period, b) final prediction error (FPE), c) Total power (TP). Bold line is the smoothed non-parametric estimation; dotted line, the parametric estimation allowing a time-varying noise variance; single line, the parametric estimation using a constant noise variance.

A similar relationship between the heart period and the noise variance for the stationary case for all subjects (Figure 1) and for the variance computed using a moving window for the nonstationary situation was obtained, although in the latest case hysteresis was observed (Figure 4).

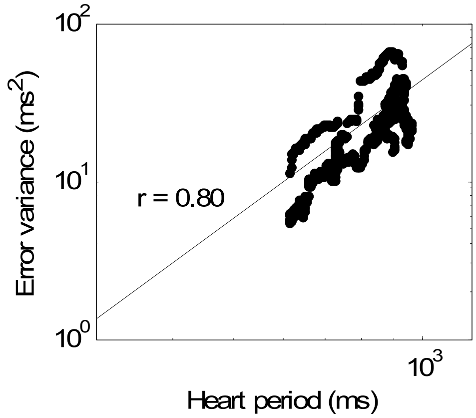

Figure 4. Relationship between the autoregressive final prediction error variance and the heart period estimated using a sliding window, for the nonstationary maneuver of a subject.

IV. DISCUSSION

Whenever an autoregressive model is estimated for the assessment of the power spectral density in different physiological stable conditions, the noise variance is estimated for every record. In this sense, in time-varying phenomena, where the physiological conditions are changing over time, a single noise variance should not be considered.

In the stationary case, for the heart rate variability spectral analysis, differences in the final prediction error variances were found for the exercise case when they were compared with those obtained at rest condition, in supine and sitting positions. These variances are used as estimators of the driving noise variance [11], affecting the evaluation of the power spectral density in absolute units. Even more, a non linear relationship between the mean heart period and the noise variance was found, suggesting the dependency of the noise variance with the physiological condition.

Incremental exercise and early recovery are conditions where a steady state is never reached; during the exercise stage the heart rate continuously changes over time, increasing in a linear fashion as a function of the workload, while for the recovery, the heart rate decreases tending to reach the rest values.

As the heart period changes from the rest values to exercise ones, the noise variance would be expected to change as it did for the stationary case. However, for a time-varying autoregressive model approach if this is not allowed and the global noise variance is used for the power spectral density estimation, an overestimation is observed for those segments that would have low-value driving noise, as occurs during exercise. Even more, the noise variance will depend not only on the particular condition on a time-segment, but on the values of the whole maneuver, and if only a part of the maneuver is analyzed, the noise and thus the power spectral amplitude will change. In a recursive estimation of a time-varying autoregressive model, the prediction error variance is expected to change and this should be considered in the resulting spectral estimation.

The prediction error variance from the RLS adaptive estimator [3] will be affected by outliers. Other time-varying approaches to estimate a time-varying driving noise variance are not described in cited references. Even more, in most of the simulations on those papers only the model coefficients are changed while the noise variance is kept as constant or its time-variation is not mentioned.

As a simple way to estimate a time-varying noise variance, the final prediction error variance over a sliding window was used, and the spectral indexes were recomputed using the noise variance obtained at each time.

In this work, a time-frequency representation where the frequency-marginal property is held [12] was used to compare the total power values and the spectral indexes obtained form both estimators at each time. A significantly higher linear correlation was obtained when the time-varying noise variance was used to estimate the autoregressive power spectral density, not only for the total power but for all spectral indexes.

The problem of considering the noise variance as a constant is related with the observed bias. For the exercise-recovery condition, the time variations of the spectral parameters were buffered, since the exercise effect was the reduction of the spectral indexes and also of the noise variance; considering it as constant, this input decrement is not taken into account for the estimations as it is done for the stationary cases.

V. Conclusion

For stationary heart period time series, the driving noise of the autorregresive models used for power spectral estimation is related with the heart period and thus, it changes with the physiological condition. For non-stationary maneuvers, where the condition is dynamically changing, the assumption of a constant driving noise may produce a bias in the estimation of the time-varying power spectral density. Thus, a time-varying noise variance should be considered.

References

[1] Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. “Heart rate variability: standards of measurement, physiological interpretation, and clinical use,” *Circulation*, vol. 93, pp. 1043-1065, 1996.

[2] A. M. Bianchi, L. Mainardi, C. Meloni, S. Chierchia, S. Cerutti. “Continuous monitoring of the sympatho-vagal balance through spectral analysis*,” IEEE Eng. Med. Biol*., vol.16, pp. 64-73, Sep/Oct 1997.

[3] A. M. Bianchi, L. Mainardi, E. Petrucci, M. G. Signorini, M. Mainardi, and S. Cerutti, “Time-variant power spectrum analysis for the detection of transient episodes in HVR signal*,” IEEE Trans. Biomed. Eng*., vol . 40, no. 2, pp. 136-144, 1993.

[4] A. Blasi, J. Jo, E. Valladares, B. J. Morgan, J. B. Skatrud, M. C. K. Khoo, “Cardiovascular variability after arousal from sleep: time-varying spectral analysis, ” *J. Appl. Physiol.,* vol. 95, pp. 1394-1404, Jun 2003.

[5] H-L Chan, H-H Huang, and J-L Lin, “Time-frequency analysis of heart rate variability during transient segments,” *IEEE Trans. Biomed. Eng*, vol. 29, pp. 983-996, 2001.

[6] L. Keselbrener, A. Baharav, Y. Ben-Dov, S. Diamant, A. Berger, Y. Sivan and S. Akselrod, “Time-frequency decomposition of HR and BP Variability in reflex syncope,” *IEEE Computers in Cardialogy,* vol. 24, pp. 219-222, 1997.

[7] M. O. Méndez, M. J. Gaitán, S. Carrasco. “Time-frequency assessment of heart rate variability under Valsalva and Mueller maneuvers,” in *Proc. 25th Annu. Int. Conf. EMBS*, Cancun, 2003, pp. 220–223.

[8] P. Novak, and V. Novak, “Time/frequency mapping of the heart rate, blood pressure and respiratory signals,” *Med. & Biol. Eng. & Compu*t., vol. 31, pp. 103-110, 1993.

[9] V. Pichot, S. Buffiere, J.-M. Gazpoz, F. Costes, S. Molliex, and J-C. Barthelemy, “Wavelet transform of heart rate variability to assess autonomic nervous system activity does not predict arousal from general anesthesia,” *Can J. Anesth*, vol. 48, pp. 859-863, 2001.

[10] M. P. Tarvainen, P. O. Ranta-aho, P. A. Karjalainen. “An Advanced detrending method with application to HRV analysis,” *IEEE Tans Biomed Eng*, vol. 49, pp. 172-174, 2002.

[11] C. W. Therrien, *Discrete random signals analysis and statistical signal processing*. New Jersey: Prentice Hall, 1992, ch 8.

[12] G. F. Boudreaux-Bartels, “Mixed time-frequency signal transformations,” in *The transformations and applications handbook*, A. K. Poularikas, Ed. Boca Raton: CRC Press-IEEE Press, 1996.