Estimation of cardiac and respiratory rhythms based on an AMFM demodulation and an adaptive eigenvector decomposition

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ESTIMATION OF CARDIAC AND RESPIRATORY RHYTHMS BASED ON AN AMFM DEMODULATION AND AN ADAPTIVE EIGENVECTOR DECOMPOSITION

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ABSTRACT

In a goal of sleep researches, we need to estimate cardiac and respiratory rhythms on 20-second epochs of a signal giving the variations in radial arterial pressure. This signal is amplitude and frequency modulated by cardiac and respiratory contributions. The technique we developped combines an amplitude and frequency (AMFM) demodulation using Teager energy operator and an adaptive eigenvector decomposition. The interest of the method lies in its independence from artefacts obtained for reasonable calculation and memory costs. Results indicate a close correspondence between estimations and reference values both for cardiac and respiratory estimations (mean error of 4% for both and standard deviation of 7% for cardiac and 14% for respiration rhythm).

1. INTRODUCTION

1.1 Context of the study

Today, numerous people suffer from sleep disturbances. The only way to detect them is to spend a night in a sleep laboratory, recorded by a specific sleep analysis system, a polysomnograph. But this is quite unpleasant for the patient as it is restrained with numerous wires. Moreover, it is an expensive method as it requires an expensive equipment and hours of a specialist to process the night recordings, even with the help of an automatic scoring system. To prevent these drawbacks, an efficient help could be supplied by actimeters. These ones consist of a wrist strap case that measure wrist movements. But today, they can only distinguish sleep from awake (actually *patient moving* or *patient not moving*). It provides interesting information on sleep quality but not enough for the detection of several sleep disorders [1, 2].

In this context, we are currently developping an actimeter that can distinguish groups of sleep stages : Awake / Light Slow Wave Sleep / Deep Slow Wave Sleep / Rapid Eye Movement (REM) sleep. To do that, a wriststrap that can measure the wrist temperature, its tigthtening strength, the wrist movements and the radial arterial pressure variations has been developed.

To perform a sleep analysis from these data, it is needed to estimate cardiac and respiratory rhythms from 20-second epochs of the arterial pressure signal. An example of such a signal is given in figure 1. Each peak corresponds to a heart beat. In addition, a periodicity of about five seconds can be observed. In fact, lungs volume influences the venous return of the blood and so modulates the amplitude of the arterial pressure. This phenomenon is at the origin of the observed periodicity. Moreover, the rhythm of heart beats is modulated by respiration. Indeed, the mechanical constraints imposed by the lungs to the heart influence its rhythm. This phenomenon is called the *Respiratory Sinus Arrhythmia*. Thus, cardiac and respiratory information is carried by the arterial pressure signal by the way of its amplitude and frequency modulations. In our context, we had to find a method for estimating these parameters that is as less complex as possible, in terms of memory and computation, since the system is to be embedded within a wrist strap watch.

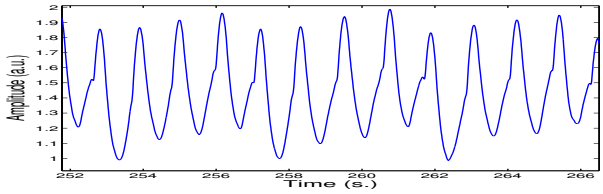

Figure 1: Example of blood pressure variations signal

1.2 Signal modelling

For the reasons given above, it is possible to model the arterial pressure signal of figure 1 by an amplitude and frequency modulated sinusoid as given below:

$$a(t)\cos[\phi(t)] = a(t)\cos\left(\omega_c t + \omega_m \int_0^t q(\tau)d\tau + \theta\right) \qquad (1)$$

where $q(t) \in [-1;1]$. The amplitude modulation ($a(t)$) is linked to the variations in the venous return while the frequency modulation ($q(t)$) can be linked to the compression of the heart operated by lungs.

1.3 Demodulation

One way of demodulating an AMFM modulated signal is to use Teager-Kaiser energy operator. Its continuous definition, applied to a continous signal named $x(t)$ is [3]:

$$\psi[x(t)] = \left(\frac{\mathrm{d}x(t)}{\mathrm{d}t}\right)^2 - x(t)\left(\frac{\mathrm{d}^2x(t)}{\mathrm{d}t^2}\right) \qquad (2)$$

$$= [\dot{x}(t)]^2 - x(t)\ddot{x}(t). \qquad (3)$$

This operator can, under some conditions, perform an amplitude and/or a frequency demodulation. More precisely,

this operator can extract the amplitude modulant signal and the instantaneous frequency signal from the modulated signal.

We describe in this paper how we used this Teager operator and an adaptive eigenvector decomposition to estimate cardiac and respiratory rhythms. The following part presents the flowchart of the method, and each step is detailed. Results are given in section 3.

2. PROCESSING LINE

The system we used to retrieve cardiac and respiratory rhythms from the arterial signal is given in figure 2.

2.1 General overview

The arterial signal is bandpassed in order to limit the influence of the noise. Next, an AMFM demodulation is performed so as to get the instantaneous frequency of the signal, which mean value gives an estimation of the cardiac rhythm. This latter is then used by an adaptive finite impulse response (FIR) filter to suppress the cardiac component in the original signal. Finally, another adaptive operation estimates the maximum eigenvector of the residual signal ($r(t)$). A simple period estimation of this latter gives the respiratory frequency.

2.2 Cardiac frequency estimation

Let us examine how AMFM demodulation can be performed using Teager operator. Only a quick overview is given here and interested readers can find details in [3, 4].

2.2.1 Theoretical algorithm

The expression of an AM-FM modulated signal, $x(t)$, is given in equation (1). Maragos et al. demonstrated that, if $2\omega_a^2 + 0.5\,\omega_m\omega_f\mu_q \ll (\omega_c - \omega_m)^2$, then :

$$\psi[x] \approx a^2(t)\omega_i(t) \text{ , in average} \tag{4}$$

where ω_a (respectively ω_f) is the maximum angular frequency in the spectrum of the amplitude (respectively frequency) modulant $a(t)$ (respectively $q(t)$). ω_m is the frequency modulation index and ω_c is the angular frequency of the carrier. Moreover, it is shown in [3, 4] that if the following constraints, where $\mathcal{O}(z)$ means the magnitude order of z, are fulfilled:

$$\mathcal{O}(\omega_a\omega_i^3) \ll \mathcal{O}(\omega_i^4) \tag{5}$$
$$\mathcal{O}(\omega_m\omega_f\omega_i^2) \ll \mathcal{O}(\omega_i^4) \tag{6}$$
$$\mathcal{O}(\omega_f^2\omega_i^2) \ll \mathcal{O}(\omega_i^4) \tag{7}$$

then we have $\psi[\dot{x}(t)] \simeq a^2(t)\omega_i^4(t)$ and instantaneous frequency and amplitude can be estimated by:

$$\omega_i(t) \simeq \sqrt{\frac{\psi[\dot{x}(t)]}{\psi[x(t)]}} \tag{8}$$

$$|a(t)| \simeq \frac{\psi[x(t)]}{\sqrt{\psi[\dot{x}(t)]}} \tag{9}$$

Thus, $a(t)$ is directly linked to the respiratory signal and $\omega_i(t) = \omega_c + \omega_m q(t)$ is an image of the respiratory signal, centered on cardiac frequency.

2.2.2 Discrete Algorithm

Notice that above-mentionned considerations deal with continuous signals. Several algorithms have been developped for discrete ones and we chose to use DESA-1a [4]. In this algorithm, $x(t)$ and its derivative $\dot{x}(t)$ are replaced with:

$$x(t) \longmapsto x(n) \tag{10}$$
$$\dot{x}(t) \longmapsto (x(n) - x(n-1))/T_s \tag{11}$$

where T_s is the sampling frequency. In this configuration, $\psi[x(t)]$ becomes the following $\psi[x(n)]$:

$$\psi[x(n)] = \left(x^2(n-1) - x(n)x(n-2)\right)/T_s^2 \tag{12}$$

2.2.3 Theoretical conditions

However, AMFM demodulation can only be performed if constraints (5), (6) and (7) are fulfilled. Yet, in our application, the first one and the last one are not. However, in a previous study [5], we reported that the error made in the demodulation step was not annoying, since we are just interested in the mean value of the instantaneous frequency.

2.3 Cancellation of the cardiac component

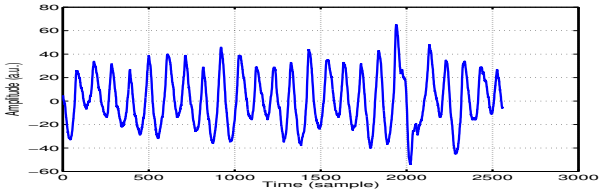

Figure 3: A 20-second epoch of the arterial pressure variations signal

Once cardiac rhythm is estimated, the cardiac component is suppressed from the arterial signal. Technically, a sinusoid at cardiac frequency ($F_c(n)$) is generated and a half-a-second-length adaptive FIR filter, using an NLMS algorithm, adapts it to the original signal in such a way that the residual signal $r(n)$ is mainly composed of the respiratory signal. Figure 4 shows the output of this step, when applied to the signal given in figure 3. As one can see, the respiratory frequency is given by the main spectral component of the signal. We chose not to use a Fast Fourier Transform for its computation and memory costs. Nor could we use a simple technique such as zero-crossing since, depending on how efficient the cardiac cancellation step has been, respiratory contribution is not always as important and readable as the one of figure 4.

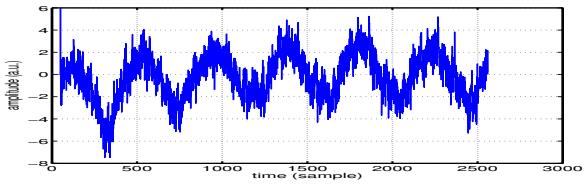

Figure 4: Residual signal $r(t)$ after the cancellation of cardiac contribution in the signal given in figure 3

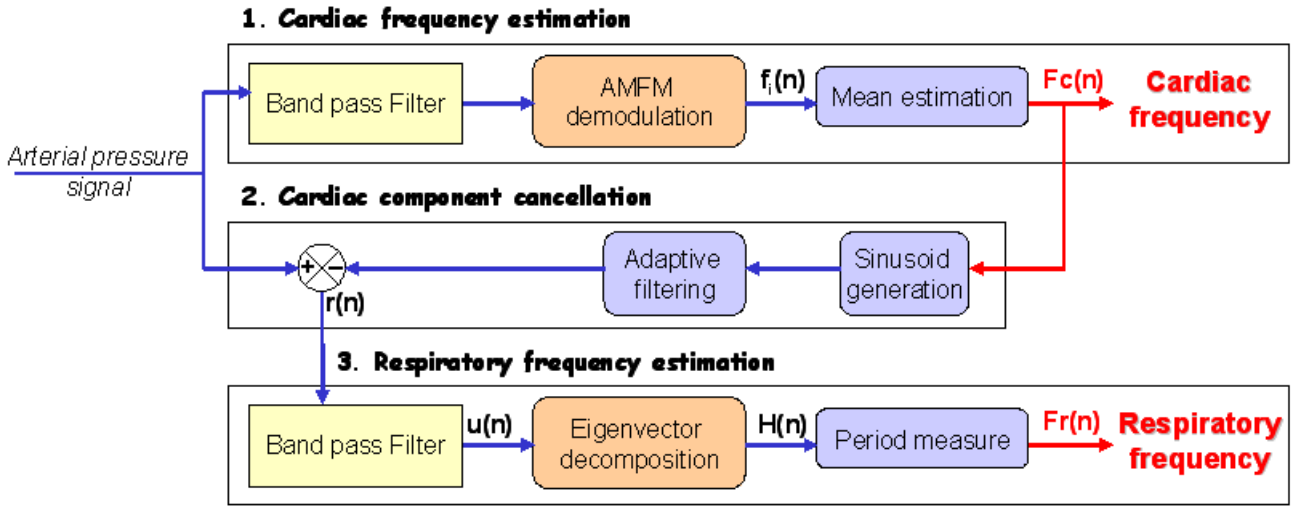

Figure 2: Processing line for the estimation of cardiac and respiratory frequencies

2.4 Respiratory frequency estimation

An interesting way of estimating the maximum contribution of a signal is given by the Kahrunen-Loeve decomposition. This latter indicates that a L-length signal $U(n)$ can be re-written as following : $U(n) = \sum_{l=0}^{L-1} c_l(n)\mathbf{q}_l$, where $\mathbf{q}_l$ are the eigenvectors of the covariance matrix $\mathbf{R}(n) = E\left[U(n)U^T(n)\right]$ and c_l are given by $c_l = \mathbf{q}_l^T U(n)$ for any $l \in [0, L-1]$.

An approximation $\hat{U}(n)$ of $U(n)$ can be obtained by summing only the first p eigenvectors, associated to the p largest eigenvalues : $\hat{U}(n) = \sum_{l=0}^{p-1} c_l(n)\mathbf{q}_l$. Thus, only the components associated with the largest eigenvalues, and representing the major part of information, are kept. Details are truncated. In our application, we assess that the respiratory frequency represents the major component of $U(n)$ and we isolate it by keeping only the eigenvector associated to the largest eigenvalue of the decomposition ($p = 1$). We will refer to it as the *maximum* eigenvector. The problem is now to compute it efficiently and fast enough.

Let us examine the system of figure 5. In this system, $y(n) = H^T(n)U(n)$ where $U(n) = [u(n), u(n-1), \ldots, u(n-L+1)]$, with L being the filter order and $H(n) = [h_0(n), h_1(n), \ldots, h_{L-1}(n)]$, the filter weights. We define the constraints $d(n) = 0$ and $\|H(n)\| = 1$, for any n. Now, let us examine the variance of the output:

$$\begin{aligned} E[y^2(n)] &= H^T(n)E\left[U(n)U^T(n)\right]H(n) \\ &= H^T(n)\mathbf{R}(n)H(n) \\ &= \frac{H^T(n)\mathbf{R}(n)H(n)}{H^T(n)H(n)}, as\ \|H(n)\| = 1\ \forall n \quad (13) \end{aligned}$$

The right term in expression (13) is called *Rayleigh quotient*. Yet, a known mathematical result about it indicates that for a symmetrical $\mathbf{R}$ matrix which eigenvalues are λ_{max},...,λ_{min}:

$$\lambda_{max} \geq \frac{H^T\mathbf{R}H}{H^TH} \geq \lambda_{min}\ , \forall H \neq 0 \quad (14)$$

Thus, if at a time n, $E\left[y^2(n)\right]$ is maximized, then we have $E[y^2(n)] = \lambda_{max} = H^T(n)\mathbf{R}(n)H(n)$. And using Lagrange multipliers, it can be demonstrated the following equations:

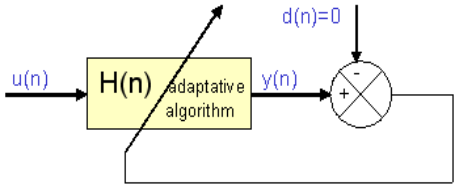

Figure 5: Adaptive *maximum* eigenvector estimation

$$\lambda_{max} = H_{max}^T\,\mathbf{R}\,H_{max} \quad (15)$$

$$\mathbf{R}\,H_{max} = \lambda_{max}\,H_{max} \quad (16)$$

and we deduce from equations (15) and (16) that when $E\left[y^2(n)\right]$ is maximized, $H(n)$ is the eigenvector associated with λ_{max} that is to say the *maximum* eigenvector. The way we maximized $E[y^2(n)]$ is the gradient method. For each new sample $u(n)$, $H(n)$ is adjusted in the following way:

$$\begin{aligned} G(n) &= H(n) + \mu\frac{\partial y^2(n)}{\partial H(n)} \\ &= H(n) + \mu\, y(n)\,[U(n) - y(n)H(n)] \quad (17) \\ H(n+1) &= \frac{G(n)}{\|G(n)\|}\ \text{(constraint)} \quad (18) \end{aligned}$$

Provided μ and the filter order are correctly chosen, the convergence is obtained and $H(n)$ is an estimation of the main component of $U(n)$. This technique, applied to the signal given in figure 4 yields the estimation of figure 6. Then, a simple method such as a period estimation can provide a precise estimation of its frequency. Notice that the higher the sample frequency is, the more precise the estimation is.

3. RESULTS

To asses the quality of the estimation, we developped a specific wrist strap. This latter recorded the four signals

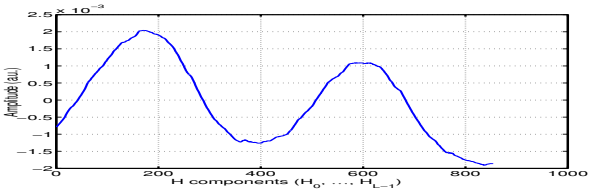

Figure 6: *Maximum* eigenvector estimation of the signal given in figure 4

detailed in section 1.1 at a 128Hz sample frequency on a 32Mo SmartMedia card. Cardiac and respiratory reference frequencies were given by a medical polysomnograph. Estimations and comparisons were made off-line. In the results presented here, we used a 50-order NLMS filter for cardiac cancellation with an adaptive step size of 0.8 and a 800-order filter with a step size of 10^{-3} for the *maximum* eigenvector estimation.

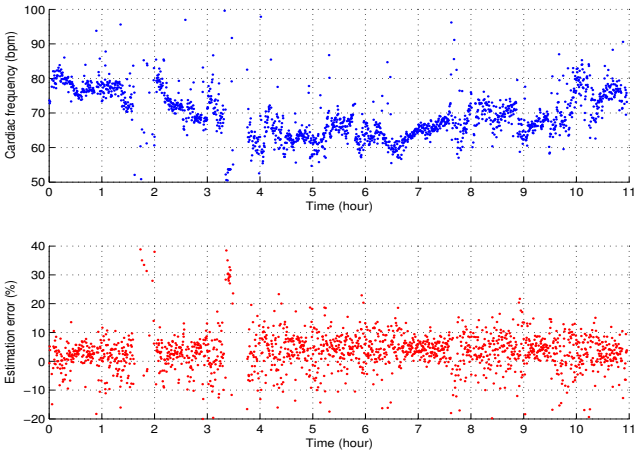

Figure 7: Reference value of cardiac frequency (up, in beats per minute) and estimation error (down, in %) during a night recording

Figure 7 gives the reference values (up, in beats per minute, bpm) and estimation errors (down, in %) of cardiac frequency led on a night recording. Notice that some parts of the signal are not analysed because of movements. It can be noticed that the mean relative error, given by $(\hat{F}_c - F_c)/F_c$, is small. Indeed, it is 4% that is to say cardiac estimation is overestimated of 4%. The standard deviation is 7% which indicates that estimation errors are mainly around this mean. Moreover, it can be observed that these errors do not depend on cardiac rhythm.
Similar behaviour is observed in figure 8 representing the estimation of respiratory frequency. We found a mean overestimation of 4% and a standard deviation of 14%.

4. CONCLUSION

In this article a new technique to estimate cardiac and respiratory frequencies from an arterial pressure signal has been presented. Even if results given here were made using a high sampling frequency, some preliminary results, not

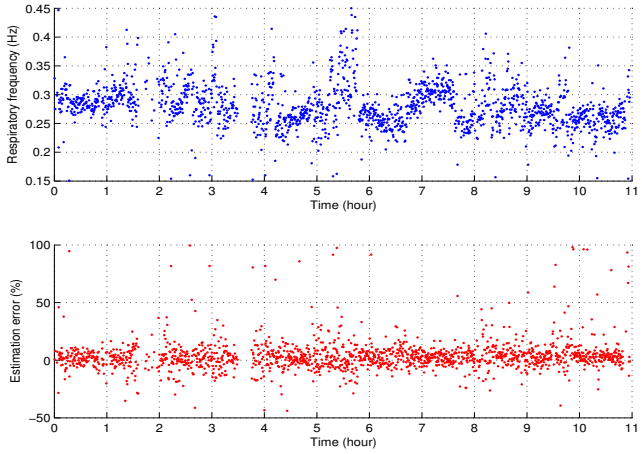

Figure 8: Reference value of respiratory frequency (up, in Hz) and estimation error (down, in %) during the same night recording

printed here, indicate that the same behaviour can be obtained at much lower sampling frequencies. Nevertheless, it is to be noticed that the lower the sampling frequency is, the less precise the estimation of respiratory frequency is.
This cardiac and respiratory frequencies estimator will be used in an automatic and portable sleep scoring system currently being developped. This latter, as comfortable as an actimeter will be more powerfull as we hope making it able to distinguish between wakefullness, light sleep, deep sleep and REM sleep. Such a system can be usefull for detecting sleep disorders as well as for everyday life allowing to improve one's well-being by monitoring one's own sleep.

REFERENCES

[1] A. SADEH, P.J. HAURI, D.F. KRIPKE, and P. LAVIE, "The role of actigraphy in the evaluation of sleep disorders," *SLEEP*, vol. 18, no. 4, pp. 288 – 302, 1995.

[2] S. ANCOLI-ISRAEL, R. COLE, C. ALESSI, M. CHAMBERS, W. MOORCROFT, and C.P. POLLAK, "The role of actigraphy in the study of sleep and circadian rhythms," *SLEEP*, vol. 26, no. 3, pp. 342 – 392, 2003.

[3] P. MARAGOS, J.F. KAISER, and T.F. QUATIERI, "On amplitude and frequency demodulation using energy operators," *IEEE Transactions on Signal Processing*, vol. 41, no. 4, pp. 1532 – 1550, April 1993.

[4] P. MARAGOS, J.F. KAISER, and T.F. QUATIERI, "Energy separation in signal modulations with application to speech analysis," *IEEE Transactions on Signal Processing*, vol. 41, no. 10, pp. 3024 – 3051, October 1993.

[5] S. BRUNO and P. SCALART, "Extraction des rythmes cardiaque et respiratoire par demodulation amfm," in *Proceedings of the 19th colloque GRETSI*, September 2003, vol. 3, pp. 355 – 358.