Improving Performance of Bio-radars for Remote Heartbeat and Breathing Detection by using Cyclostationary Features

Daniel Malafaia, José Vieira and Ana Tomé
IEETA, Universidade de Aveiro, Aveiro, Portugal

Keywords: Signal Detection, Cyclostationarity, Bio-radar, Software Defined Radio, Cognitive Radar.

Abstract: In this paper we present a continuous wave radar created using a software defined radio platform that uses doppler effect to measure the heart-rate and breathing. The measurements are evaluated using a classic energy detection method and a cyclic spectrum estimation technique, then the two methods are compared. The results show that by taking advantaging of the cyclic autocorrelation of the bio-signals we can get better detection than the usual energy detection.

1 INTRODUCTION

Bio-radar technology aims the combination of the radar and biomedical measurements to achieve the detection of vital signals (such as respiration and heartbeat) without using electrodes or sensors. The use of this wireless method to gather bio-signals allows a variety of applications such as medical monitoring of contagious patients, wireless stress measurement and even, with high transmitted powers, surveillance and rescue missions where bio-radars would allow to locate trapped people under debris.

The development of bio-radars have been following two strategies: Continuous Wave (CW) Radar and Ultra Wide-band (UWB) Radar(Zhang et al., 2012). The CW was the first method for bio-radars, been first proposed in 1978 and different hardware has been developed since then(Griffin, 1978).As the transmitter is continuously broadcasting the total power on the target is maximized. In the other hand UWB radar uses repeated pulses witch allows to obtain extra information about the position of the target, that is impossible to obtain in a CW radar.

There has been a large and fast development in the area of SDR where versatile and portable hardware platforms can be found. The SDR is a highly configurable platform where the majority of the processing is achieved digitally. The input (receiver) and the output (transmitter) parts of the SDR are reconfigurable in order to allow the use a wide band of the spectrum.

The usage of a SDR as an radar allows for the development of cognitive radars(Haykin, 2006), this kind of radars can be aware of the environment and make an intelligent use of the spectrum allowing the usage of multiple radars without cross interference as we can allocate a different frequency for each one.

2 DOPPLER RADAR FOR BIO-SIGNALS

2.1 How the Doppler Radar Works

A doppler radar is a system that by directing a microwave signal to an object that is not stationary and listening to the reflexion can infer it movement characteristics by analyzing how the frequency of the signal sent was altered by the object's motion. This frequency variation is due to the Doppler Effect and is described by

$$f_r = f_t \frac{(1+v/c)}{(1-v/c)} \tag{1}$$

where f_t is the transmitted frequency, f_r is the shifted frequency due to the Doppler Effect, v is the object speed and c is the speed of light.

This shift in frequency can also be seen as a phase difference between the transmited and recieved signal. So if an object is at a d_o distance the phase difference ϕ of the generated signal and the received is given by,

$$\phi = \frac{2d_o 2\pi}{\lambda} \tag{2}$$

Malafaia D., Vieira J. and Tomé A..
Improving Performance of Bio-radars for Remote Heartbeat and Breathing Detection by using Cyclostationary Features.
DOI: 10.5220/0005287603440349
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2015), pages 344-349
ISBN: 978-989-758-069-7
Copyright © 2015 SCITEPRESS (Science and Technology Publications, Lda.)

where λ is the wavelength of the transmitted signal. If an object is then changing it's position then the distance change will be perceived by the radar as a phase variation.

2.2 Doppler Detection in a CW Bio-radar

In a CW bio-radar the system is constantly transmitting a sinusoid in the direction of the target, then this signal will be reflected by the person. Therefore any small movements of the chest will introduce phase changes on the refleced signal accordingly. These changes are then going to be small if the chest is inflated and larger if the chest is deflated. The signal received is then mixed with the original sinusoid in order to compare the two phases.

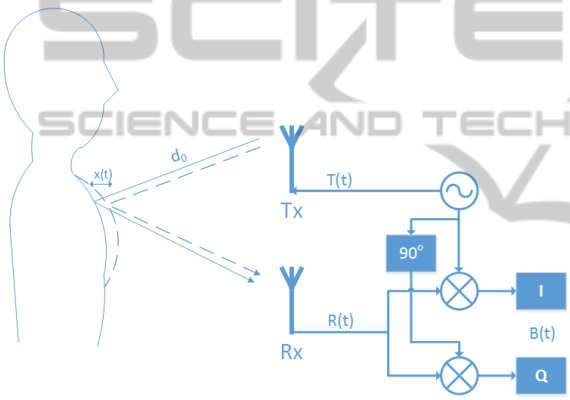

Figure 1: Bio-radar taking advantage of the doppler effect to detect the movement of the chest.

Considering the transmited signal , $T(t) = cos[2\pi ft + \phi(t)]$ with f the frequency of operation and where ϕ copes the unavoidable phase noise. As show in Figure 1 this signal is transmitted to the subject at a distance d_0 from the device. The reflected signal is modulated by the physiological movement $x(t)$ (as the heartbeat and respiration). If we neglect amplitude variations, we will have the following equation for the received signal in our bio-radar(Li et al., 2013),

$$R(t) \approx cos[2\pi ft - \frac{4\pi d_0}{\lambda} - \frac{4\pi x(t)}{\lambda} + \phi(t - \frac{2d_0}{c})] \quad (3)$$

where c will be our wave electromagnetic speed and λ it's wavelength. So the received signal is then a time delayed version of the transmitted signal with a phase modulation created by periodic motions of the target. At the receiver the signal is demodulated back to the baseband,

$$B(t) = cos[\theta + \frac{4\pi x(t)}{\lambda} + \Delta\phi(t)] \quad (4)$$

where $\theta = 4\pi d_o/\lambda + \theta_o$ is given by the subject distance and the θ_0 phase shift at the reflection surface. The $\Delta\phi(t) = \phi(t) - \phi(t - 2d_o/c)$ is then the residual oscillator phase noise. By then analyzing the angle, every parameter will be constant except to the varying physiological movement and the phase noise. Has we want only to acquire the bio-signals we can then filter the angle according with the signal that we want to obtain.

Usually the common human values for this kind of signals are for the respiration 0.1Hz to 0.8Hz and for the Heart Rate 0.8Hz to 2Hz (Hø st Madsen et al., 2008). The result of applying two filters in order to adquire the two cardiorespiratory signals, to the angle of $B(t)$ in a typical test is seen in Figure 2.

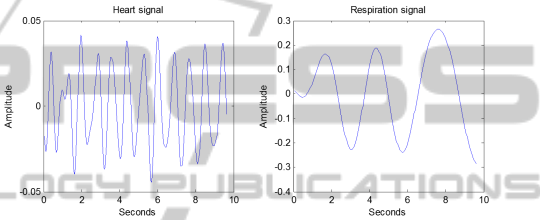

Figure 2: Signals obtained by a Bio-Radar.

The breathing pattern has a higher amplitude value than the heartbeat, this is due to the large movement of the torso during the breathing that is relatively greater than the slightly movements produced by the beat of the hearth. Also is visible the almost constant periodicity of the two, with a lower period to the heartbeat and higher one for the respiration.

3 CYCLOSTATIONARITY BASED DETECTION

3.1 Detection of Bio Signals using Cyclostationarity

As the cardiorespiratory signals show periodicity in their behavior we can then take advantage of this characteristic in order to achieve a better detection. One way to analyze this periodic signals, and as they show an approximately periodic auto-correlation is to use a cyclostationarity analysis methods.

In order to identify the presence of a cyclostationary digital signal in a given sampled spectrum we usually use two mathematical operations, cyclic autocorrelation and cyclic spectrum. These two methods will show unique features when in presence of a cyclostationary-based signal.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

3.2 Basic Notions of Cyclic Autocorrelation

To understand cyclic autocorrelation we first need to define what's correlation. Correlation is a mathematical operation that allows us to measure the degree to which two signals are similar and is the expected value of the inner product of the two signals. For the autocorrelation the procedure is similar, but instead of having two different signals we use the inner product of the signal with itself at a different time. We know by the definition of a cyclostationary signal that the autocorrelation of a signal,R_x, is periodic, lets define that period by being T_0 and the lag being τ, then:

$$R_x(t+T_0,\tau) = R_x(t,\tau) \tag{5}$$

If a periodic correlation exits then it can be proved (Gardner et al., 2006) that $x(t)$ and it's frequency-shifted version $x(t)e^{j2\pi n/T_0 t}$ are correlated for any $n \in \mathbb{Z}$.Then we can define the cyclic autocorrelation being:

$$R_x^\alpha(\tau) \triangleq E\{x(t+\tau)x^*(t)e^{-j2\pi\alpha t}\} \tag{6}$$

with $\alpha = n/T_0$ and $*$ being the conjugate. Expanding the equation we have:

$$R_x^\alpha(\tau) = \lim_{T\to\infty} \frac{1}{T}\int_0^T x(t+\tau)x^*(t)e^{-j2\pi\alpha t}dt \tag{7}$$

Now as we have a cyclostationary signal with a periodic autocorrelation in T_0 we don't need to integrate the inner product of the signal with itself delayed to infinity as we did in (7), we can limit it to T_0:

$$R_x^\alpha(\tau) = \frac{1}{T_0}\int_0^{T_0} x(t+\tau)x^*(t)e^{-j2\pi\alpha t}dt \tag{8}$$

It's possible now to detect if a stochastic process x(t) exhibit cyclostationarity at the cycle frequency α if $R_x^\alpha(t) \neq 0$ (Gardner et al., 2006).

3.3 Discrete Time Cyclic Autocorrelation

For a computational implementation we need a discrete time cyclic autocorrelation function as we are going to use discrete values. So from (7) we can then derive the discrete time cyclic autocorrelation that is:

$$R_x^\alpha(\tau) = \lim_{N\to\infty} \frac{1}{N}\sum_{n=0}^{N-1} x(n+\tau)x^*(n)e^{-j2\pi\alpha n} \tag{9}$$

where N is the number of samples that we are using. As in pratical usage we are going to use a limited number of samples we then remove the limit from the equation and we have the aproximation:

$$\widetilde{R}_x^\alpha(\tau) = \frac{1}{N}\sum_{n=0}^{N-1} x(n+\tau)x^*(n)e^{-j2\pi\alpha n} \tag{10}$$

Note that $R_x^\alpha(t)$ can be computed efficiently using the FFT of the product $x(n+\tau)x^*(n)$ (Madisetti and Williams, 1999).

3.4 Cyclic Spectrum

Another tool for analyzing cyclostationarity is the cyclic spectrum. To derive this function we do something very similar to the Wiene-Khinchin theorem (Gardner et al., 2006) but applied to cyclic autocorrelation from (7). The cyclic spectrum is then:

$$\widetilde{S}_x^\alpha(f) = \frac{1}{N}\sum_{n=0}^{N-1} \widetilde{R}_x^\alpha(\tau)e^{-j2\pi f\tau} \tag{11}$$

with $f = \pm\alpha/2$. That, once again, is nothing more than the Fourier Transform of the cyclic autocorrelation and can be calculated with a two dimensional FFT of the previously calculated cyclic autocorrelation.

4 PRACTICAL EXPERIMENT

4.1 System Setup

The main part of this bio-radar system is the B200, a software defined radio system developed by Ettus that allows full duplex use, so we can send and receive RF signals at the same time, making it a good choice for a CW radar.

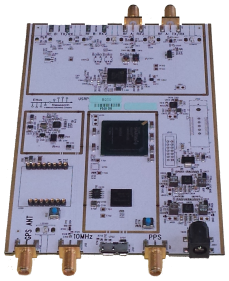

Figure 3: USRP B200 board.

This board uses the Analog Devices AD9364 chip that concentrates almost all the RF front-end, with mixers for the Rx and Tx with incorporated VCO and PPL that share the same reference clock,

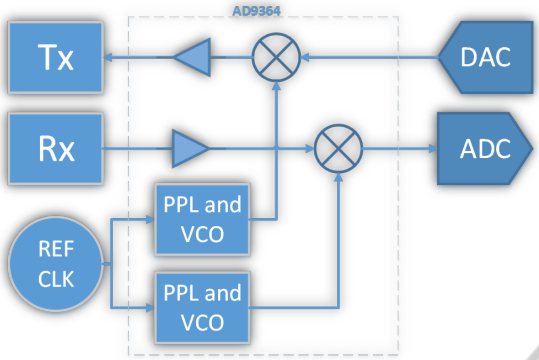

Figure 4: RF frontend of B200.

this allow for homodyne detection allowing to avoid any fluctuations in the mixer frequency.

In order to maximize the gain and reduce noise, we connected to the B200 two directional antennas.

Figure 5: The bio-radar system.

The whole system will then operate as a CW radar at the frequency of $2.7GHz$ with a emitting power of approximately 5mW with the minimum sampling frequency allowed by the system of $62.5kSPS$.

The B200 has an automatic DC rejection system, so if we want to share the same frequency on the transmitter and receiver we need to slight offset in the frequency our emitted wave, for this purpose a digital $\Delta = 1kHz$ sinusoid is generated and then passed to analog trough the DAC and mixed with the $2.7GHz$ carrier, then allowing for the system to use the same central frequency both mixers.

At the receiver the ADC will be running at $62.5KSPS$ sampling $62.5KHz$ of the $2.7GHz$ centered spectrum.At digital domain we got a digital down converter that will pass our signal to the baseband, removing the 1KHz offset added in order to avoid the DC rejection system. At the base band we then work with start working with the phase of the signal, by filtering it trough a anti-aliasing low pass filter and decimating by 2500 in order to get a 25Samples/s signal. We then filter this signal trough two band-pass filters, one in order to obtain the breathing from $0.1Hz$ to $0.8Hz$ and another for the Heart Rate from $0.8Hz$ to $2Hz$. The filters used are 1000-order hanning finite impulse response.

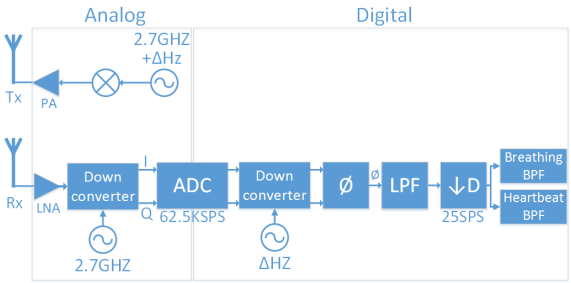

Figure 6: System Diagram.

The person under test will then be seated at approximately 1meter from the system, facing frontally to the directional antennas.

4.2 Procedure

After the initial setup of the system and with the person seated we start recording. The subject is asked to breath 3 times and then stay in apnea as longer as possible to then breath normally. After that, the subject will then leave the range of the system and do some fast paced exercise for about 20 seconds. When the exercise is finished the evaluation resumes and the subject is asked again to breath 3 times, stay in apnea as longer as possible and then breath normally.

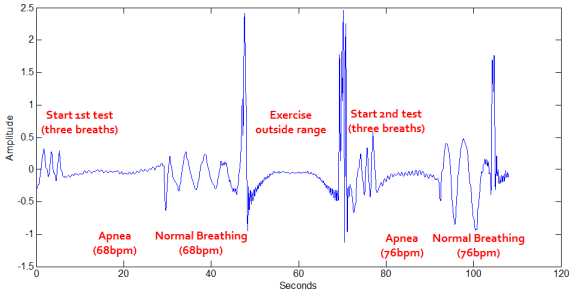

Figure 7: Standard testing used in this article.

4.3 Results

By using samples at the output from the heartbeat band-pass filter we can then test the detection methods in order to compare the performace of both.Two methods were tested:

- Cyclostationary detection: the cyclic spectrum of the signal is calculated and the frequency with

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

higher value give us the frequency of the signal.

- Classic energy detection: we use a energy detection in frequency, where we search for a peak in the DFT of the data.

To obtain the features that we will use for the cyclostationary detection we used the cyclic spectrum in a part of the signal where the subject is in apnea at 68bpm to obtain the heartbeat features. For the breathing pattern the we use the part of the signal after the first apnea.

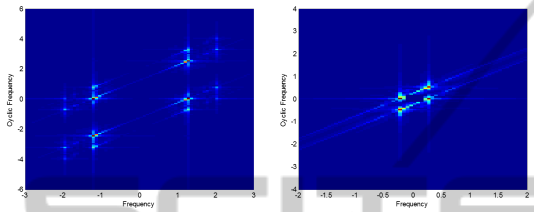

Figure 8: Cyclic spectrum for the heartbeat(in the left) and for the breathing (on the right).

We will compare the performance for the hardest signal to detect, the heartbeat, but the same procedure can be demonstrated, with similar results, for the respiratory signal.

To detect the heartbeat frequency from the cyclic spectrum we locate the maximum value at the cyclic spectrum plane instead of using a traditional energy detection method where we detect the peak of the DFT of the signal.

To prove that the cyclostationary method shows better results than a traditional energy detection in frequency, white gaussian noise is digital added at the signal in order to simulate various SNRs situations.

In order to simulate the behavior of the system under various SNR levels, we first calculate the SNR of the acquired heartbeat signal, that in our case is near 10dB. Once we have this value we can calculate the power that the digitally added white gaussian noise needs to have in order to simulate a determined SNR,

$$P_{anoise} = 10log_{10}(-10^{SNR_o/10} + 10^{SNR_e/10}) - P_{signal} \quad (12)$$

where SNR_o is the SNR of the original signal, SNR_e the SNR that we want to achieve, P_{signal} is the power of the bio-signal and finally the P_{anoise} is the power of the noise that we need to add.

By using Monte Carlo method we determined the probability of detect the same heartbeat frequency as the original signal shows but for various SNR levels. This procedure used 550 samples at $25SPS$ of a relaxed person at 68bpm for 5 to -25dB of SNR each one tested 500 times for added gaussian white noise.

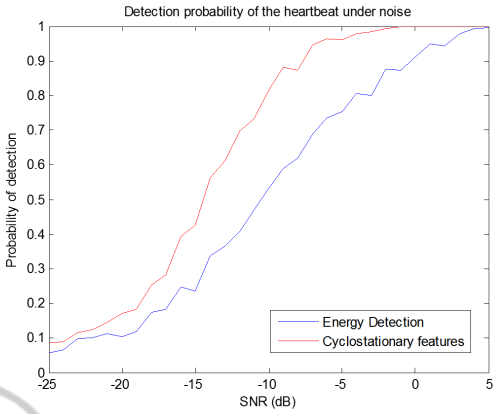

Figure 9: Performance comparative of both methods.

The comparison is the following,

It's visible that the cyclostationary based detection show better results than energy detection. For probabilities of detection higher than 80% we are looking for improvements in the order of 6dB.

SCITEPRESS SCIENCE AND TECHNOLOGY PUBLICATIONS

5 CONCLUSIONS

It's feasible to use a software defined radio to build a bio-radar and acquire both respiration and heartbeat. This open doors to the use of commercial Software Defined Radios has a platform to implement Cognitive Bio-Radars. The results show that a cyclostationary analysis based on the cyclic spectrum improve performance on this type of radars comparatively to simple energy detection schemes. The performance could be further improved by using a digital phase-locked loop system.

REFERENCES

Gardner, W. a., Napolitano, A., and Paura, L. (2006). Cyclostationarity: Half a century of research. *Signal Processing*, 86(4):639–697.

Griffin, D. W. (1978). MW interferometers for biological studies. *Microwave Journal*, 21:69–71.

Haykin, S. (2006). Cognitive radar: a way of the future. *IEEE Signal Processing Magazine*, 23(1):30–40.

Hø st Madsen, A., Petrochilos, N., Boric-Lubecke, O., Lubecke, V. M., Park, B.-K., and Zhou, Q. (2008). Signal Processing Methods for Doppler Radar Heart Rate Monitoring. In *Signal Processing for Knowledge Extraction and Information Fusion*. Springer-Verlag.

Li, C., Lubecke, V. M., Member, S., Boric-lubecke, O., and Lin, J. (2013). A Review on Recent Advances in Doppler Radar Sensors for Noncontact Healthcare Monitoring. 61(5):2046–2060.

Madisetti, E. V. K. and Williams, D. B. (1999). Giannakis , G.B. "Cyclostationary Signal Analysis". chapter 17.

Zhang, Y., Jiao, T., Jing, X., Li, Z., Li, S., Yu, X., Lv, H., Zhang, Z., and Wang, J. (2012). A detecting and identifying method for two stationary human targets using single-channel ultra-wideband radar. *EURASIP Journal on Advances in Signal Processing*, 2012(1):202.