Wavelet-Based Analysis of 60 GHz Doppler Radar for Non-stationary Vital Sign Monitoring

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***Abstract*—We propose here a Doppler-radar implementation at 60 GHz for contactless monitoring of vital signs (respiration and heartbeat). In order to provide a real-time detection of non-stationary vital signs and critical events, an estimation technique is here used by means of a wavelet transform of the received signals. Moreover, the amplitudes of the relevant vital movements can be deduced by the wavelet transform so as to distinguish the useful signal from noises and non-desired movements.**

***Index Terms*—Non-stationary vital-sign monitoring, Doppler radar, Wavelet, 60 GHz.**

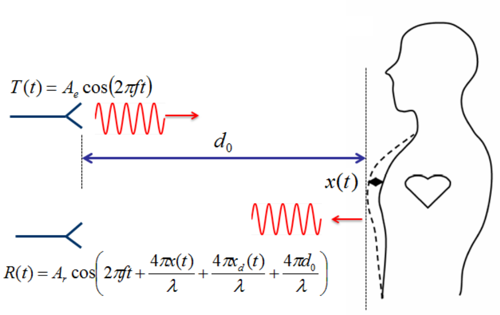


Figure 1. Representation of the CW Doppler radar system.

I. Introduction

The progressive population aging motivates the expansion of home-care services and of reliable technological tools in order to provide constant monitoring of elderly people, avoid accidents, and reduce costs related to hospitalization. A real-time detection of vital signs is believed to offer important information on the health condition of the patient, thus preventing critical events or acting in a timely and effective manner after them [1].

We propose here a 60 GHz implementation of a Doppler-radar system illuminating a person and being capable to detect its respiratory rate (RR) and heartbeat rate (HR) in an indoor environment. The detection is done by means of the Doppler frequency-shift due to the body micro-movements (see Fig. 1), having in general a non-stationary behavior. In order to obtain a real-time detection of the vital parameters, the observation is performed over a time-window shorter than the periodicity of the signals. This will definitely deteriorate the frequency resolution if spectral components are computed by means of Fourier transform techniques. For this reason, a suitable strategy is here proposed, guaranteeing both time and frequency resolution, based on a wavelet analysis of the received signal. The wavelet transform is in fact capable to distinguish among signal components having different time scales.

After an introduction on wavelet transforms, the detection method is described and numerical results are shown and discussed.

II. Theoretical Framework

In this section we give a few mathematical details about the continuous wavelet transform (CWT) analysis and describe its application to our signal detection.

A. *Continuous wavelet transform*

The CWT $WT(t, a)$ of a signal $s(t)$ is the convolution between $s(t)$ and a scaled mother function $\psi(\frac{t}{a})$. $\psi(t)$ is dilated if the scale factor $a > 1$ and compressed if $0 < a < 1$ [2]. The time–dependent signal $s(t)$ is then decomposed into a multi–resolution, or time–scale (frequency) domain:

$$WT(t,a) = \frac{1}{\sqrt{a}} \int s(u)\psi^{*}\left(\frac{u-t}{a}\right) \mathrm{d}u. \qquad (1)$$

The two–parameter dependency of the CWT makes it possible to study $s(t)$ simultaneously in time and frequency domain.

Among the many choices available for the mother wavelet, the Morlet wavelet has been already successfully implemented to detect the heartbeat signal from a Doppler radar [3], and it will be used also in this study. The standard Morlet wavelet is defined as a complex exponential wave modulated by a Gaussian envelope,

$$\psi(t) = \pi^{-1/4} \exp(i\omega_0 t) \exp\left(-t^2/2\right), \qquad (2)$$

where ω_0 is the central frequency of Morlet function. The instantaneous frequency f_u in the scaled mother $\psi(\frac{t}{a})$ can be written $f_u = \omega_0/(2\pi a)$: low frequencies give a better resolution in frequency, while high frequencies give a better resolution in time.

B. Estimation of heartbeat and respiratory signal

Adult people RR lies in the range $0.2 - 0.5$ Hz [4], and HR in the range $1 - 1.7$ Hz [5], never exceeding 3 Hz. Consequently, the lower band from $f_r^{\min} = 0.2$ Hz to $f_r^{\max} = 0.5$ Hz is associated to the RR, and the higher band from $f_h^{\min} = 1$ Hz to $f_h^{\max} = 3$ Hz to the HR. At each time t, the HR and RR are estimated as

$$\begin{aligned} f_r^{\text{est}} &= \underset{f\in[f_r^{\min}, f_r^{\max}]}{\arg\max} \; |WT\left(t, f/2\pi\omega_0\right)|^2, \\ f_h^{\text{est}} &= \underset{f\in\left[f_h^{\min}, f_h^{\max}\right]}{\arg\max} \; |WT\left(t, f/2\pi\omega_0\right)|^2, \end{aligned} \tag{3}$$

where arg max h is the frequency value where the function h assumes its maximum. We assume also that physiological movements have always larger intensities than the noise. As described in Fig. 1, each vital signal is modeled as a sine wave. Once the frequencies are determined by using (3), the relevant amplitudes can be deduced in closed-form from the value of $WT(t, a)$. These expressions, not reported here for the sake of brevity, have been derived for the first time, and are fundamental in order to establish the correctness of the estimation. In fact, typical known values can be used to distinguish physiological movements from noise and other random body movements.

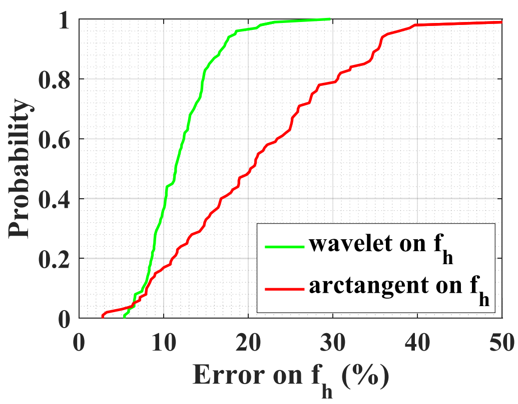
III. Numerical Results

In this section we show the cumulative distribution functions (CDF) relative to 1000 estimations of the respiration and heartbeat frequencies f_r and f_h. A signal-to-noise ratio of 10 dB is chosen as a realistic figure in practical Doppler radars. Amplitudes and frequencies take random values with Gaussian distribution, within the realistic ranges mentioned above. The time observation window is fixed at 10 s. In order to simulate non-stationary vital signs, f_h is randomly varied every two seconds, with a variance of 0.2 Hz, while the value of f_r is constant.

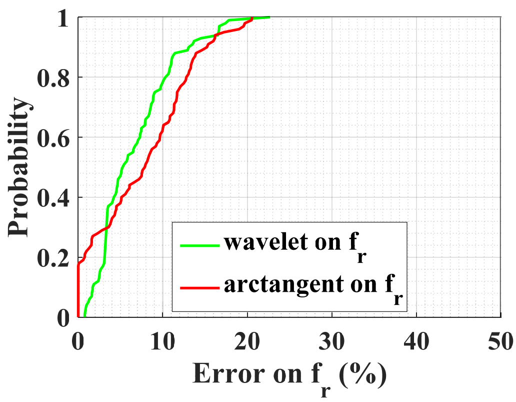
In Fig. 2, CDF curves are compared between different methods. An "arctangent" Fourier-transform analysis [6] is used as a reference, and the wavelet approach is implemented. Wavelets provide a significant detection improvement if an accuracy of 10-20 % is considered, as is typically required in clinical applications. The improvement is particularly visible on the estimation of the HR, while both the methods lead to similar performance for the RR, since the RR has been modeled by a stationary signal.

IV. Conclusion

In this paper we have applied a wavelet transform algorithm to a Doppler-radar estimating both HR and RH for a real-time monitoring, characterized by observing the non-stationary signal during short periods of times. A significant improvement has been verified through numerical simulations. Further studies will focus on experimental verifications and the impact of random body movements.



(a)



(b)

Figure 2. CDF obtained with the wavelet and the arctangent methods, related to the frequencies (a) f_h and (b) f_r .

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