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# Non-Contact Estimation at 60 GHz for Human Vital Signs Monitoring Using a Robust Optimization Algorithm

Ting Zhang<sup>[1,2]</sup>, Guido Valerio, Julien Sarrazin

Sorbonne Universités, UPMC Univ Paris 06<sup>[1]</sup>  
UR2, L2E, F-75005, Paris, France  
ting.zhang, guido.valerio, julien.sarrazin@upmc.fr

Dan Istrate

Biomechanics and Bioengineering (BMBI)<sup>[2]</sup>  
CNRS UMR 7338, Sorbonne Universités  
Université de Technologie de Compiègne  
F-60200, Compiègne, France  
mircea-dan.istrate@utc.fr

**Abstract**—This paper presents an approach to estimate body movements related to vital activities by means of a 60 GHz Doppler radar, using robust optimization algorithms. Several different scenarios are simulated and numerical reconstruction results are reported. The optimization algorithm is shown to be more convenient and less sensible to perturbations than a direct spectrum analysis of baseband signal.

## I. INTRODUCTION

Doppler radar has been widely applied in the medical domain in the recent years [1]. This non-contact technique is very popular and interesting as no sensor is needed on the body. Physiological movements, such as those related to the heartbeat and breathing, can be detected and evaluated by measuring the frequency shift of the reflected signal according to the well known Doppler-effect law. However, due to the nonlinear nature of the Doppler phase modulation, undesired intermodulations of harmonic components are present [1]. A direct peak detection from the spectral analysis is therefore no more reliable, since ambiguities can arise when interpreting the different peak locations. Furthermore, we show that mutual phasing between the physiological movements can have an impact on the frequency detection, and should be correctly taken into account for.

This paper is organized as follows: the theory of frequency shift measurement in Doppler radar is summarized at first. The influence of initial phases on the measurement is then discussed. Simulated results of optimization algorithms are finally presented and compared with the direct spectrum analysis.

## II. THEORY

In a CW (Continuous Wave) Doppler detection system for vital signals, a sinusoidal signal  $T(t) = A_e \cos(2\pi ft)$  at carrier frequency  $f$  is transmitted towards a human body, and then reflected by the chest wall which moves according to the heartbeat and respiration. The reflected signal is demodulated by an IQ quadrature receiver to avoid detection issues due to lack of reception during certain intervals of time [2]. The complex baseband signal is modulated by tiny physiological

movements  $x(t)$  of the human body. Here, two principal physiological movements (heartbeating and respiration) are represented by a single tone sinusoidal signal, respectively,  $x(t) = x_r(t) + x_h(t) = m_r \sin(\omega_r t + \phi_r) + m_h \sin(\omega_h t + \phi_h)$ , where  $m_r$  and  $m_h$  describe the amplitudes of respiration and heartbeat movement, respectively,  $\omega_r$  and  $\omega_h$  represent the movement frequencies,  $\phi_r$  and  $\phi_h$  are the initial phases.

The exponential term of the reflected baseband signal can be expanded using Fourier series [1],

$$B(t) = \sum_{n=-\infty}^{+\infty} \sum_{k=-\infty}^{+\infty} J_n \left( \frac{4\pi m_h}{\lambda} \right) J_k \left( \frac{4\pi m_r}{\lambda} \right) \exp [j (n\omega_h t + k\omega_r t)] \exp [j (n\phi_h + k\phi_r)] \exp (j\psi), \quad (1)$$

where  $J_n$  is the  $n$ -th order Bessel function of the first kind.  $\lambda = c/f = 5$  mm is the working wavelength of the CW radar at 60 GHz.  $\psi$  is defined as the total residual phase of the system. This complex baseband signal in the frequency domain is represented by a sum of harmonic components, which causes not only creation of harmonic frequencies for each physiological movement signal itself, but also generates intermodulated frequencies between the two movements [1]. Here, we address influence of the initial phases  $\phi_r$  and  $\phi_h$  on the baseband spectrum. Suppose that some harmonic component of respiration is equal, or very close to the fundamental or harmonic of the heartbeat,  $\omega' = n'\omega_r \approx k'\omega_h$ . Then the Fourier coefficient at  $\omega'$  is represented as

$$B(\omega') = J_{n'} \left( \frac{4\pi m_h}{\lambda} \right) J_0 \left( \frac{4\pi m_r}{\lambda} \right) \exp (jn'\phi_h + j\psi) + J_0 \left( \frac{4\pi m_h}{\lambda} \right) J_{k'} \left( \frac{4\pi m_r}{\lambda} \right) \exp (jk'\phi_r + j\psi), \quad (2)$$

where the amplitude depends not only on  $m_r$  and  $m_h$ , but also on  $\phi_r$  and  $\phi_h$ . This condition is here referred to as an “ambiguity”, as it makes the accurate detection of these two physiological movements more difficult. This issue will be numerically addressed in the next section.

### III. NUMERICAL RESULTS

In this section, simulation results are presented. Two different spectral estimation methods are discussed and compared to recognize both the respiration and heartbeating rhythm.

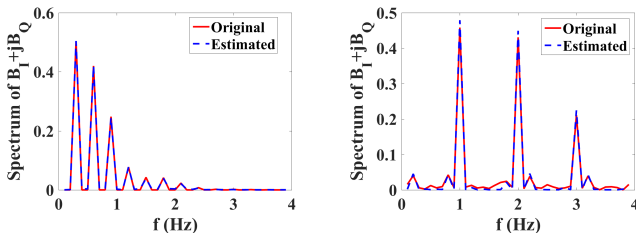
#### A. Spectral analysis

Firstly, we take the heartbeating rate at  $f_h = 1.2$  Hz (normal resting heart rate for healthy adults ranges from 1 Hz to 1.7 Hz) and the respiration rate  $f_r$  at 0.3 Hz (typical values are 0.2–0.33 Hz), where an ambiguity exists. The acquisition time is  $T = 10$  s, and the sampling frequency is  $F_s = 100$  Hz. The displacements are  $m_r = 1.0$  mm and  $m_h = 0.08$  mm, which correspond to the detection from the front of human body [3]. We can deduce that the first peak in the spectrum in Fig. 1 (a) (red line) corresponds to the fundamental of respiration. The values of  $f_h$ ,  $m_r$  and  $m_h$  can be deduced from the spectrum if the mutual phasing is not considered, i.e.  $\phi_r = \phi_h = 0$  in (1), as in [1]. However, when considered, the spectrum changes and it is thereby not possible anymore to retrieve  $f_h$ .

Furthermore, cases exist where the heartbeat fundamental is completely blurred by the intermodulation, which forbids the direct spectral analysis. For instance, in an emergency situation where a person breathes more rapidly, his breathing rate increases. In Fig. 1 (b), such a case is illustrated with  $f_r = 1$  Hz, other parameters being unchanged. The heartbeat fundamental is not visible, hence the direct spectral analysis does not work at all, as the spectrum depends on several unknown parameters,  $f_r$ ,  $f_h$ ,  $m_r$ ,  $m_h$ ,  $\phi_r$ , and  $\phi_h$ , which persuades us to find a better spectrum-estimation algorithm.

#### B. Optimization procedure

To measure body movements using an optimization algorithm, we propose the Genetic Algorithms (GAs). In our case, the GAs is used to optimize a defined cost function, which describes the discrepancy between the measured baseband signal spectrum and the one calculated by a direct signal model, where the baseband signal is defined as the same form as (1). The first example is shown in Fig. 1 (a), where no measured noise is added. The reconstructed spectrum (blue dashed line) fits perfectly with the real spectrum (red solid line), implying that all unknown parameters are accurately retrieved with the GAs. Now, to further test the robustness



(a)  $f_r = 0.3$  Hz,  $f_h = 1.2$  Hz, (b)  $f_r = 1.0$  Hz,  $f_h = 1.2$  Hz, with SNR=10 dB

Figure 1. Representation of retrieved signal in the frequency domain. Original spectrum of  $B_I + jB_Q$  (red solid line); Estimated spectrum using the GAs (blue dashed line).

of the GAs, several different simulations were performed. The reconstructed values for  $m_r$ ,  $m_h$  and  $f_h$  are given in Table I. Note that the reconstructed value of  $f_r$  is directly deduced from the spectrum of the baseband, which corresponds to the first strongest peak along with the spectrum. For all scenarios presented in Table I, a random noise is added to the baseband signal, in order to ensure a received signal to noise ratio of 10 dB. Cases  $S1$  and  $S2$  correspond to the detection from the front of the body, in a normal situation. Cases  $S3$  and  $S4$  describe the detection from the back of the body. Emergency situations are given in case  $S5$ , where the person breathes very weakly ( $m_r \approx m_h$ ), and in cases  $S6$  and  $S7$ , where the respiration rate is much higher, as shown in Fig. 1 (b). Note that for all these simulations, we succeeded to get accurate heartbeating and respiration rates, even if a strong noise is present and an ambiguity occurs. Moreover, the amplitudes of induced displacements are also very close to the actual values and could be used as a complementary information for vital sign monitoring. The calculated time of this optimization procedure is about 2.5 s, which is reasonable for real-time monitoring.

Table I  
ESTIMATED PARAMETERS USING GAS: REAL AND ESTIMATED VALUES

	$m_r$ (mm)		$m_h$ (mm)		$f_h$ (Hz)	
	Real	Est	Real	Est	Real	Est
$S1$ , $f_r=0.3$ Hz	1.0	1.0	0.08	0.083	1.3	1.291
$S2$ , $f_r=0.3$ Hz	1.0	1.0	0.08	0.089	1.2	1.198
$S3$ , $f_r=0.3$ Hz	0.2	0.189	0.08	0.084	1.3	1.296
$S4$ , $f_r=0.3$ Hz	0.2	0.194	0.08	0.062	1.2	1.198
$S5$ , $f_r=0.3$ Hz	0.08	0.113	0.08	0.074	1.2	1.204
$S6$ , $f_r=0.6$ Hz	1.0	0.8	0.08	0.07	1.2	1.209
$S7$ , $f_r=1.0$ Hz	1.0	1.0	0.08	0.068	1.2	1.196

### IV. CONCLUSIONS

Simulated results of the detection of physiological movements by Doppler Radar at 60 GHz have been shown. An optimization algorithm, compared to the direct spectrum analysis, is proved to be more robust to deal with ambiguities.

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