Study and Evaluation of the Vital Signs Detection Based on the Third Order Cyclic Temporal Moment and Cumulant

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This work was supported by Segula Technologies (www.segulatechnologies.com).

ABSTRACT Due to the microwave sensitivity toward small movements, non-contact and non-invasive continuous monitoring radar, has been pointed out as one of the most promising technologies for estimation of human cardiopulmonary activity. Various signal processing methods have been proposed in the literature to extract the heart rate (HR) and respiratory rate (RR). Although the RF-reflected signal from the human body is corrupted by noise of the environment, random body movements and clutter. Given these limitations, the interest information RR and HR might be strenuous to extract. In this purpose, cyclostationary approach has been use for non-contact detection of vital signs. However, the preliminary works focus only on one frequency and do not include the impact of other parameters (attenuation and random movement of the body) in the analysis. In this paper, we evaluate a wide range of several parameters that might influence on the cyclic features of the reflected signal from the person’s chest. Besides, we inspect the assessment of the third orders cyclic features of the cyclostationary signal processing performance by developing the third cyclic temporal moment and the third cyclic temporal cumulant. The analysis is carried out using a reduced number of samples to reduce the response time and complexity of system radar for three ISM frequencies 10, 17 and 26 GHz. To validate and assess the performances of the simulation part, we carried out a series of tests on a clothed person seated in a laboratory environment. All of the results obtained make it possible to consider a setting guide for a better estimation of RR and HR.

INDEX TERMS Cyclostationary statistics, third-order cyclic moment, third-order cyclic cumulant, vital signs, heart rate, respiration rate.

I. INTRODUCTION

In the topic of improving the driver assistance system and the working conditions of drivers while increasing the safety and reliability of traffic, the short-distance monitoring of driver activity in a vehicle is a major challenge to prevent accidents, as well as to improve the driver’s health. The non contact detection of vital signs aims to predict general physical health of a driver’s condition: lack of attention, stress, fatigue, insomnia, sleepiness, etc, and to develop alternative solutions for controlling driver vigilance. These parameters altering the driver’s vigilance are directly linked to physiological signals such as heart rate and breathing rate. Therefore, each driver has a unique and different value of this signs and the normal ranges of a person’s vital signs vary with age, weight, gender, and overall health.

Non-contact physiological monitoring can have a significant impact beyond healthcare applications, particularly in situations where direct subject access is not available or difficult. Radio Frequency (RF) radars have been used in wireless sensors applications for decades. Compared to other technologies, wireless radars are interesting for their benefits of non-contact and non-invasive detection based on RF. The advantages of non-contact vital signs detection by radar methods have been demonstrated in [1], [2]. The main of the radar for monitoring vital signs based on the detection of the mechanical movements that occur due to periodic physiological events, including heart and respiration rates. These vital signs are estimated from the acquired waveform that reflects the chest volume variation and displacement during the inspiration and expiration.
The first use of radar systems for the detection of vital signs dates back to the 1975 s for measuring the respiration of a rabbit located at 30 cm [3], the system was not sensible enough to detect the heartbeat. Besides that, the heart beats was measured with a breath hold required [4]. Since then, the interest in radars for the monitoring of breathing and heart rate has increased considerably. An interferometric radar based on the six-Port receiver technique for vital sign detection is presented [5]. Two scenarios of the position of the radar was investigated. The first one, the system has been placed approximately half a meter in front of the person sitting on a car seat, pointing directly on its thorax. The second one, the sensor has been installed on the backside of the car seat, while the antenna is aiming on the back of the person. In [6], an impulse Ultra-Wide Band (UWB) radar for detecting the minute chest movement was introduced. Two signal processing methods are designed and evaluated for on-line and off-line analysis by investigating 16 different radar positions in a vehicle for robust breathing rate monitoring under the circumstance of body motions during driving. While in [7], the same type of radar was used for car crash prevention.

These developments involved analog and digital signals processing to separate the small heart signal from the much larger respiratory signal, so that the person does not need to hold their breath for the heart rate to be measured, and the heart and breathing can be measured simultaneously [8]. The output signals are then fed to different filtering technologies [8]–[12]. The selection of a filtering technique depends on the type, the order and the cutoff frequencies of each filter, in order to separate the cardiac signal from the respiratory signal.

To solve the harmonic problem, the wavelet transform (CWT) [13] combined with either empirical mode decomposition (EMD) was introduced in [14]. In [13], the author proposed a wavelet transform based data length variation technique for the purpose to realize fast detection of heart rate utilizing CW Doppler radar. Compared to the traditional Fast Fourier Transform (FFT) method, the accuracy is improved dramatically, because the proposed method is able to distinguish respiratory harmonics from the heartbeat signal by examining the peak property of the combined wavelet frequency spectrum. A wearable nonlinear tag and an intermodulation-based nonlinear sensor operating in both Doppler and frequency shift keying (FSK) modes was proposed in [15] for the elimination of harmonics and clutter rejection.

Despite non-contact vital sign analysis has been studied in the last two decades along with a lot of successful methods have been reported, the impacts of low signal-to-noise ratio, clutter noise and harmonic interference are still challenging matters in non-contact vital signs detection field. In the case of a low Signal-to-Noise Ratio (SNR) and body motion interference, the modulated back-scattered radar signal is non-stationary with hidden periodicities, which lead to use a nonlinear transformation based on cyclic statistics which is the cyclostationarity theory [16], [17].

This research works of Somayeh Kazemi et al. are carried out to investigate this approaches, by employing simulations tools to estimate the Spectral Correlation Function (SCF) along with a large number of samples. In [18], the high order of the cyclostationary was exploring. In spite of that, the authors describe the higher-order cyclostationary for a zero mean value signal. This simplification makes the second temporal cyclic cumulants and the third order cyclic temporal cumulants both equivalent to their respective cyclic moments, but may not in fact be true in our case of signal reflected from the chest’s person. For this type of signal, the mean value is non-zero. Therefore, the second cyclic cumulants and the third cyclic cumulants are different from their cyclic moment.

In this paper, we propose a continuation of the work previously carried out in the article [19], concerning the exploration and evaluation of the first and second-order cyclostationary approach. This article deals with the development of the third order temporal cyclic moment and the third order cyclic cumulant of the reflected signal. In order to verify the detection performance of our proposed method based on the third order cyclostationary algorithm, a series of simulations while considering different parameters are performed to compare the theory and the results of the simulations. This parametric study is performed with the aim of providing a comprehensive guide for the detection of vital signs with the CW radar using the third-order cyclostationarity. In the last part, an example of measurement at the frequency 10 GHz is presented to validate the simulation part. Other measures will be presented in future work.

This paper is organized as follows. In Section 2, the theory of the cyclostationary approach is detailed. The comparison between the FFT and the proposed algorithm are shown in Section 3, while the theoretical development of the cyclic features of the received signal is shown in the Section 4. A series of simulations and discussions to form a parametric study are carried out in Section 5. Example of measurement is shown in section 6, while the conclusions is drawn in Section 6.

II. GENERAL THEORY OF CYCLOSTATIONARY PROCESS

Cyclostationary processes, sometimes called periodically stationary processes, are special cases of non-stationary processes in the sense that their statistical properties vary over time but in a periodic manner. These cyclostationary processes are generally generated by systems with random output and periodically disturbed over time. Let x(t) be a continuous time random process with complex values, x(t) is a cyclostationary process of order m if and only if its statistical properties up to order m vary periodically in time. It is mean that a time-series is considered to be m-th order wide sense cyclostationary if its m-th order time varying temporal cyclic moment and cyclic cumulant are periodic in time. Both cyclic moments and cumulants are useful to characterize an m-th order cyclostationarity of signal [20].

The first part of this section focuses on introducing the models of the investigated waveforms. The second part is
dedicated to a thorough theoretical analysis of the CS features of the investigated waveforms, and the derivation of their third order cyclic moment and cumulants analytical form.

- **Cyclic Temporal Moment Function CTMF:**
  
  $M^m_x[\tau]_{m,p}$ defines the m-th order Cyclic Temporal Moment Function (CTMF) [21]:
  
  $$M^m_x[\tau]_{m,p} = \lim_{N \to \infty} \frac{1}{N} \sum_{n=0}^{N-1} L_x[n, \tau]_{m,p} \exp(j2\pi \alpha \tau)$$  

  where

  $$L_x(n, \tau)_{m,p} = \prod_{j=1}^{n} x^{(s)}[n + d_j]$$  

  is m-th order lag product of the signal $x(t)$. $A_{\alpha} = \{ |\alpha| L_x[\tau]_{m,p} \neq 0 \}$. It should be noted that the set of discrete cyclic frequencies $A_{\alpha}$ is defined as $\alpha \in [-\frac{1}{2}, \frac{1}{2}]$, where the cyclic resolution is of order $\Delta \alpha = \frac{1}{N}$.

- **Cyclic Temporal Cumulant Function CTCF:**

  The n-th order cyclic temporal cumulant function (cyclic cumulant) is a Fourier coefficient of the cyclic temporal cumulant function. The cyclic cumulants are pure sine-wave amplitudes, and they can be computed by combining cyclic moment amplitudes.

  $C^m_x[\tau]_{m,p}$ defines the m-th order Cyclic Temporal Cumulant Function, and is a Fourier coefficient such that:

  $$C^m_x[\tau]_{m,p} = \lim_{N \to \infty} \frac{1}{N} \sum_{n=0}^{N-1} \sum_{\{ d \}} \exp(j2\pi \nu \tau)$$

  where

  $$A_{\nu} = \{ \nu \mid C^m_x[\tau]_{m,p} \neq 0 \}$$

  denotes the entire set of cyclic frequencies.

  In this paper, we will use the CTMF to CTCF conversion formula, which allows the derivation of cyclic cumulants directly from the data and that is what we will use in our algorithm. The cyclic cumulants isolate the cyclic feature of the m-th order from products of lower orders. Hence, all possible products of lower-order pure sine-waves can be subtracted from the m-th order cyclic moment sine waves to obtain the cyclic cumulant of order m [21]. The conversion formula is expressed as follow:

  $$C^m_x[\tau]_{m,p} = \sum_{D_m} \left[ (\pm 1)^k k! \sum_{\{ a \}} \prod_{i=1}^{d} R^a_x[\tau_{bi} | m,p] \right]$$  

  where $k = d - 1$, $\nu$ is the pure sine wave of the lower order cyclic frequencies and $\alpha$ is the impure sine-wave of order m. The vector of cycle frequencies $\alpha$ is the vector of cyclic temporal moment cycle frequencies, and they must sum up to the cyclic-cumulant cycle frequency $\nu$.

  In the equation (4), the sum is over distinct partitions of the index set $\{ 1, \ldots, m \}$, referred to as $D_m$, $d$ is the number of elements in a partition, $1 \leq d \leq m$. The set of indexes belonging to a partition is denoted as $\{ b_i \}_{i=1}^d$. 

### III. COMPARISON BETWEEN THE FAST FOURIER TRANSFORM AND THE CYCLOSTATIONARY ALGORITHM

This section provides a comparison and explanation of our proposed approach and an existing approach in the literature based on the calculation of the Fourier transform associated with filtering. This technique consists of filtering the received signal with a Butterworth 4th order filter, and after we calculate its FFT, figure 1 shows the results of the probability of detection of the respiratory and heart rate with this algorithm and the algorithm of cyclostationary. To extract heart and respiratory beats, the most important power peaks are equivalent to heart and respiration rates. We use the baseband signal at the 10 GHz frequency with a sampling frequency of 100 Hz and a number of points of 6001 at the distance of $d = 1$ m.

By comparing these two methods, it emerges that the cyclostationary algorithm is more efficient for the detection of both heart and breathing rates than the FFT associated with the filter.

### IV. CYCLIC FEATURES OF VITAL SIGNS

The cyclostationarity algorithm will be validated initially by representing the cardiac signal by an ECG and the respiratory signal by a sinusoidal wave, modeling the signals resulting from a detection with contact. Subsequently, our algorithm will be applied to a non-contact case (necessary case) in which the respiratory and cardiac signals will be modeled each one by a sinusoidal signal. The signal have been generated using MATLAB.

#### A. CYCLIC FEATURES IN THE CASE OF DETECTION WITH CONTACT

Modeling the heartbeat is an essential step for the automatic identification of characteristic waves of the chest movement in the case of detection with contact. Having a priory no mathematical model to specify cardiac activity, we sought to establish an approximate model to use in our Matlab codes while respecting the values described in [22]. This representation of waves would consist in describing the signal by its amplitude at each instant for each wave constituting the cardiac signal. The data used for the generation of the
sequence of events and waves in a cardiac cycle is based on [22].

The reflected signal is essentially composed of a respiratory component in the sinusoidal form, and a cardiac component close to the shape of the signal given by the electrocardiogram (see Figure (2)). The two components evolve at distinct average frequencies, namely 0.5 Hz for the respiratory rate, and 1.3 Hz for the heart rate.

B. CYCLIC FEATURES IN THE CASE OF NON CONTACT DETECTION

The process of breathing and the heartbeat generates the contraction of the muscles, which modifies the volume of the chest and arises from pressure differences between the chest and the external environment. These changes cause vibrations of the thorax and abdomen, which generate significant mechanical displacements at the surface of the skin. The chest movement $x_{HR}(t)$ is the sum of the two signals of breathing $x_r(t)$ and cardiac $x_b(t)$. These vital signs are detected by the radar transmitting electromagnetic waves $T(t)$ toward person’s chest, and recording the received reflections. The transmitted signal can be expressed as:

$$T(t) = \cos \left(2\pi ft + \varphi(t)\right)$$  \hspace{1cm} \text{(5)}

The modeling of vital signals is essential for radar analysis and simulation. In this paper, we discuss the modeling of respiratory and cardiac signals used for our simulations $x_r(t)$ and $x_b(t)$, respectively. Since the cardiac signal a priori does not have a mathematical model for specifying cardiac activity for non contact detection, we sought to establish an approximate model to use it in our Matlab codes for the first simulation.

The chest displacement $x_{HR}(t)$ varies between $a_r = 4$ mm and $a_r = 12$ mm due to RR, while it ranges between $a_h = 0.2$ mm and $a_h = 0.5$ mm due to HR [23], [24]. The baseband signal is simplified into the following equation (6):

$$B_b(t) = AM(t) \sum_{q=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} f_l^{q+l} J_q(A_r) J_l(A_h) \times \exp \left[ j2\pi (qf_r + lf_b)t \right] + Z(t)$$  \hspace{1cm} \text{(6)}

where

$$A_r = a_r \frac{4\pi}{\lambda}, \quad A_h = a_h \frac{4\pi}{\lambda}, \quad A = A_{HR}, \quad \exp \left( \frac{4\pi d}{\lambda} \right)$$

$$M(t) = \exp \left[ j \frac{4\pi x_f(t)}{\lambda} + \Delta \varphi(t) \right]$$

where $A_{HR}$ is the attenuation for the complex-valued reflected signal, $Z(t)$ is the complex noise and $x_f(t)$ is the random body motion. To mimic the effect of random body motion on vital sign detection, we used the White Gaussian Noise Model (WGN). The third-order cyclic-moment of $B_b(t)$ can be expressed as follow:

$$M_x^q(\tau_{3,p}) = \lim_{T \to \infty} \frac{1}{T} \int_{-T}^{T} B_b(t)B_b(t + \tau_1)B_b(t + \tau_2) \times \exp(-j2\pi at) dt$$

(8)

After some mathematical manipulations, the 3-th order cyclic moment of the reflected signal ca be computed as:

$$M_x^q(\tau_{3,p}) = A^3 m(t)(m + \tau_1)(m + \tau_2) \sum_{q=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} J_q(A_r) \times J_l(A_h) \sum_{q'=q}^{\infty} \sum_{l'=l}^{\infty} J_{q'}(A_r) J_{l'}(A_h) \sum_{q''=q'}^{\infty} \sum_{l''=l'}^{\infty} J_{q''}(A_r) J_{l''}(A_h) \times \exp\left[ j2\pi(f_j(qf_r + q'f_r + q''f_r + l + l' + l'') \times \exp\left[ j2\pi(f_j(qf_r + q'f_r + l + l' + l'')f_h \right] \right.$$  \hspace{1cm} \text{(9)}

where the set of cyclic frequencies is given by:

$$A_{d3} = \left\{ \pm (q + q' - q'')f_r + (l + l' - l'')f_h \right\} .$$

The third-order cyclostationary of the received signal retains the fundamental frequency along the cyclic axis. We calculate the third-order cyclic cumulant (TOCC) of the signal by using the formula (3) to convert the third-order cyclic moments to the third-order cyclic cumulants conversion since we already have the third-order cyclic moments.

The calculation of the third order cyclic temporal cumulant requires the definition of the set of partitions, which is presented in the table 1 for the order $m = 3$. The number of possible partitions increases with the order, and is given by the Bell’s number.

![FIGURE 2. $X_f(t)$ Cardiac signal ECG model.](image)

### TABLE 1. Partitions, example for $m = 3$.

| $D_m$ | $d$ | $b_1$ |
|-------|-----|-------|
| $\{1,2,3\}$ | 1 | $b_1 = \{1,2,3\}$ |
| $\{3\} \{1,2\}$ | 2 | $b_1 = \{1,2\}$, $b_2 = \{3\}$ |
| $\{1\} \{2,3\}$ | 2 | $b_1 = \{1\}$, $b_2 = \{2,3\}$ |
| $\{2\} \{1,3\}$ | 2 | $b_1 = \{2\}$, $b_3 = \{1,3\}$ |
| $\{1\} \{2\} \{3\}$ | 3 | $b_1 = \{1\}$, $b_2 = \{2\}$, $b_3 = \{3\}$ |
The cyclostationarity algorithm requires a high number of samples to accurately estimate the cyclic features of the wanted signal. Very large number of samples leads to both the computational cost and the response time of the digital signal-processing block that can be high. In the [17] results are obtained using 131,072 samples. One of our primary objective is to require cyclic features, by reducing the measurement time and the numbers of samples which is in our case 8001 samples.

V. SIMULATION AND DISCUSSIONS
This section presents the simulation results of detecting the respiratory rate (RR) and heart rate (HR) of humans in both cases: with contact and non contact detection. We define the amplitude and the frequency of the respiratory and cardiac signal to build the signal which describes the movement of the rib cage. This description will allow to have the baseband signal reflected by the chest of the person under test. We exploit the third order cyclostationary features to acquire the values of the heart and the respiratory rate. Which relies on the derivation of the third order cyclic moment and cumulants from the received signal. The features are extracted considering attenuation, as well as body motion, in the presence of a white Gaussian noise. The detailed algorithm for the extraction of RR and HR is given in Algorithm 1. For the first part of the simulation, we apply the algorithm on the received signal while modelling the cardiac signal with an ECG for detection with contact, and in the second part the cardiac signal is modeled by a sinusoidal signal for a non contact detection.

Algorithm 1 Algorithm for Extraction of RR and HR

1) Define the parameters of the heartbeat and the breathing signals: $a_c, a_h, f_r$ and $f_h$
2) Construction of the chest signal $x_{HR}(t)$ by combining heartbeat $x_h(t)$ and breathing signal $x_r(t)$: $x_{HR}(t) = x_h(t) + x_r(t)$
3) Construction of the baseband signal $B_h(t)$
4) Application of the cyclostationarity algorithm: the third order cyclic moment and cyclic cumulant
5) Bandpass filter used over the frequency range from 0.16 Hz and 0.33 Hz correspond to the normal respiratory rate [25], [26] (10 bpm to 20 bpm)
6) Extraction of the maximum in the range of the bandpass filter which correspond to the RR
7) Suppression of the harmonics of RR
8) Bandpass filter used over the frequency range from 0.83 and 1.5Hz correspond to the normal heart rate [25], [26] (50 bpm to 90 bpm)
9) Extraction of the maximum in the range of the bandpass filter which correspond to the RR

A. SIMULATION OF THE CYCLIC FEATURES FOR DETECTION WITH CONTACT OF VITAL SIGNS
This session is dedicated to the simulation part in the case of detection with contact, by modeling the heart rate by an ECG. Figure (3) represent the third order cyclic temporal moment and cyclic temporal cumulant of the received signal in the case of a signal without the additive noise. As can be seen the figure, all the cyclic frequencies of interest are present and the number of samples is sufficient to reconstruct the cyclic spectrum for each feature.

Figure (4) represents the third order cyclic temporal moment and cyclic temporal cumulant of the received signal in the case of a signal with the additive white Gaussian noise. As can be seen the figure, all the cyclic frequencies of interest are present and the number of samples is sufficient to reconstruct the cyclic spectrum for each feature.

To evaluate the impact of the additive noise on detection of vital signs, in the case where the cardiac signal is modeled by an ECG signal instead of a sinusoidal. We computed the probability of detection in function of SNR for the second and the third order of cyclostationary algorithm. The Figure 5 shows the result of the simulation for the heart and the breathing detection in the both cases second and third order inf unction of the SNR.

The probability of detecting heart and respiratory rates is higher with order three than with order two of the cyclostationary approach. As the previous results, the detection of respiration is still high compared to cardiac. Even with the modeling of the heart rate with an ECG signal we arrive at the extraction of information of interest with the same precision than modeling with sinusoidal.

Taking into account the state of the art of the signal processing part and precisely, the ECG signal. For each case of pathology, the signal is defined according to the values of the amplitude and the duration of each wave constituting the ECG signal which varying the HR. Figure 6 shows example of three cases of the cardiac signal, a normal rhythm with the cardiac frequency 1.3 Hz which belongs to the normal interval and two abnormal rhythm the hypothermia with slow heartbeat frequency 0.4 Hz and the tachycardia with high heart rate 2Hz.

Figure 7 shows the third order temporal moment applied to the three different baseband signal of the three cases of
cardiac signal. In all the cases, the detection of the heart rate is possible.

**B. SIMULATION OF THE CYCLIC FEATURES FOR NON CONTACT DETECTION OF VITAL SIGNS**

This section will concern the results of simulation for non contact detection of vital signs. The third order of cyclostationary algorithm was applied on the chest movement signal. The distinct cyclic features for the cyclic moment and cumulant are defined for different cyclic frequencies. We have considered simulation values shown in Table 2 to visualised the different combination of cyclic frequencies of each order.

The first part of simulation deals with the additive noise. It concern the application of the proposed cyclostationarity algorithm on the received signal without and with additive Gaussian white noise. Figure 8 shows the third-order cyclic statistics of the reflected signal for the both cases. The set of cyclic frequencies defined from the cyclic temporal moments and the cyclic cumulant are different. For the cyclic frequencies occurring with the moment, which is the impure cyclic frequencies, it can be the result of a combination of lower order cyclic frequencies. The third order cyclic moment contain the different combination of the heart and respiration rates which is defined by the set of cyclic frequencies $A_{\alpha 3}$. All the different combination for the set, are visualized in the figure 8. The two cyclic features contain the respiratory rate $f_r = 1.3$ Hz and the heart rate $f_h = 0.5$ Hz and other frequencies as $f_h - f_r = 0.8$ Hz and $f_h + f_r = 1.8$ Hz.

The probability of detection expressed as a function of SNR was carried out. In order to better evaluate the influence of the additive noise, on detection of vital signs. The detection concern the presence of both heart and respiration rates, by checking if the estimate values using the cyclostationary algorithm $f_h'$ and $f_r'$ of HR and RR respectively, are the same values set for the transmitted signal $f_h$ and $f_r$. 

| Table 2. Parameters defined for the simulation. |
|-----------------------------------------------|
| System frequency $f$ | 10 GHz |
| Cardiac frequency $f_h$ | 0.5 Hz |
| Heart amplitude $a_h$ | 0.5 mm |
| Breathing frequency $f_r$ | 1.3 Hz |
| Breathing amplitude $a_r$ | 4 mm |
| Distance between antenna and target | 60 cm |
| Sampling frequency | 100 Hz |
| Number of samples | 6001 |
Thus we simulate both probabilities $P_d = P(f^*_t = f_r)$ and $P_d = P'(f^*_h = f_h)$. The blue curve corresponds to RR, while the red one corresponds to HR. The probability of detection of the respiration rate is $P_d = 1$ from the value of $\text{snr} = -20$ dB because the respiratory signal is the strongest component in the reflected signal. On one hand, the heart rate detection is $P_d = 1$ from the value of $\text{snr} 6$ dB. On the other hand, the probability of detection of the heart rate is increasing with the SNR.

The sampling rate is chosen to minimize the computational cost, $f_s = 100$ Hz. Hence, the signal is generated with a sampling time of $T_s = 0.01$ s, and for a total observation time $T = 60$ s, which leads to $N_s = 6001$ samples. One of our main goals is to require cyclic features by reducing the measurement time and the numbers of samples, hence we carry out our data using small sample sizes, which is reduced comparing to the number cited in the literature. It should be noted that increasing the number of samples would lead to a better estimation of cyclic features at the expense of higher computational costs, which leads to a longer processing time. The Figure 10 shows the probability of detection of the vital signs using a small number of sample. We observe that reducing the number of sample to 601 samples, leads to a bad detection of HR, because we have a small probability of detection of HR compared to the one of 6001 samples used previously in the Figure 9.

The second study concerning the impact of the distance between the subject under test and the antennas, on cyclic features detection. So from the attenuation Equation in [19] we can derive the maximum distance at which detection of vital signs is possible:

$$d_{\text{max}} = \left[ \frac{P_{T_s} G_T G_R \sigma_h L_h \lambda^2}{(4 \pi)^3 A_r^2 A_{HR_{\text{min}}}} \right]^{\frac{1}{2}}$$  \hspace{1cm} (10)

where $P_{T_s}$ is the transmitted power, $G_T$ and $G_R$ are transmitter and receiver antenna gains. $\sigma_h$ is the Radar cross-section (RCS), $L_h$ is the reflection loss of the heart. Equation (10) shows that the detection distance is related to the transmitted power, antenna parameters, as the frequency. These variables are constant and transceiver-dependent, while the target RCS $\sigma_h$ and the reflection loss $L_h$, are related to the human body.

Changing the distance between the person chest and the surface of antenna has been studied in this part. The third-order cyclic features of the received signal for the 10 GHz frequency at two distinct distances $d = 60$ cm and $d = 1.5$ m is representing are presented in the Figure 11 and Figure 12.

In these examples, HR and amplitude are equal to $f_h = 1.3$ Hz and $\alpha_r = 0.5$ mm, respectively, although RR and amplitude were $f_r = 0.5$ Hz and $\alpha_r = 4$ mm, respectively. The number of samples was set at 6001 so the sample frequency 100 Hz. In Figures, all frequencies of interest are 10, 17 and 26 GHz. The penetration of waves inside human tissues decreases at higher frequencies (greater than 10 GHz, the penetration does not exceed 3 mm) [27].

The third part of simulation, regarding the influence of the frequency system on Cyclostationary Detection. The choice of the frequency system is justified by the tendency of the system to miniaturize and belonging to the Industrial Scientific and Medical band (ISM). Three frequencies considered in this simulation 10, 17 and 26 GHz. The penetration of waves inside human tissues decreases at higher frequencies (greater than 10 GHz, the penetration does not exceed 3 mm) [27].

Figure 13 and 14 show the cyclic characteristics of the reflected signal for two frequencies 17 GHz and 26 GHz for a distance of $d = 60$ cm and 6001 points. Regarding both frequencies and the result of the frequency in the previous
FIGURE 14. Third-order cyclic temporal cumulant $|C_x(\alpha, \tau = 0)|_3$ of the reflected signal for the frequency system: (a) 17 GHz and (b) 26 GHz.

FIGURE 15. Measurement configuration considering a VNA and two horn antennas.

figures (10 GHz), all cyclic frequencies are present. Respiratory frequencies are clearly identified and correspond to expected values. However, the heart frequencies are drowned in noise. Increasing the frequency of the system is equivalent to increasing the sensitivity to small movements causing the appearance of other frequency peaks. The validation of the simulation part will be presented in the next section at the frequency 10 GHz. The validation with the measurements will carried out using the ISM frequency 10 GHz, due to the accessibility of the equipment and instrumentation in our lab that can cover this frequency range. A detailed analysis is proposed in the next section.

VI. EXPERIMENTAL VALIDATION

The figure 15 presents the vital signs measurements built up with a reference measurement system, i.e., vector network analyser (VNA 24 from Rohde and Schwarz R&S, 0.7–24 GHz) interfaced with two horn antennas (AH Systems SAS-571 Double Ridge Horn Antenna 700 MHz–18 GHz through stable coaxial cables with 2 m long each. The bandwidth is 100 Hz. The number of points taken for the signals measured with the VNA is 8001 points, which corresponds to a duration of 80 seconds.

Figure 16 shows The amplitude and the phase-shift of the complex transmission coefficient $S_{21}$ at the operating frequency 10 GHz and input power $-6$ dBm. Considering the antenna gain (11.56 dB) and cable losses of 3 dB, the source power $-6$ dBm corresponds to a radiated power of $-3.56$ dBm. The distance between the person under test and the antenna aperture is varied (50 cm, 1 m and 2 m).

Figures (17) and (18) show the third order cyclic moment and cyclic cumulant of the complex coefficient of transmission $S_{21}$, applied in the interval corresponds to the breathing rate and heart rate, respectively.

Simultaneously with the VNA, ECG and airflow sensors are used as references to extract the RR and HR, in order to compare with the rates extracted by applying the cyclostationary process for precision calculation. The relative error analysis was performed on the measured data to estimate the reliability of the third order cyclostationary process. The Table 3 shows the respiration and the heart rates calculated from the third-order cyclostationarity and the reference measurement system, thus the errors for input power $-6$ dBm at different distance. The relative errors increase by increasing the distance.
The relative error for the detection of RR AND HR is very low in the case of short distance 50 cm. While the relative error for the detection of RR and HR <3(%) for the two distances 1 m and 2 m. This difference is due to the attenuation. The RR is detectable with considerable accuracy for any distance, because it is less affected by noise (environment noise, interference motion body, etc.) as well as the HR. The results show that increasing the distance between the antenna and the chest decreases the accuracy of the vital signs detection specially for the HR.

VII. CONCLUSION

We have presented the high order cyclostationary statistical approach for the estimation of the respiration and the heart rates. The algorithm developed in this paper, is based on the third order cyclostationarity approach, which allows to calculate the cyclic statistics of the reflected baseband signal like the cyclic temporal moment and the cyclic temporal cumulant. The analytical closed-form of the third order cyclic temporal moment and cyclic temporal cumulants of the baseband signal reflected from the chest of the person under test are first derived. Then validated for both cases of detection with contact while modeling the cardiac signal with an ECG, and non contact by representing the cardiac and breathing signal by a sinusoidal for each one. The results of simulations obtained by this method are very encouraging. This method is very tough in the face of noise without any demodulation of the reflected signal from the chest’s person.

The work presented in this paper is a feasibility study, allowing to validate the concept of detection of vital signs through the third order of cyclostationarity algorithm (cyclic moment and cyclic cumulant). Indeed, a more in-depth study on the measurement environment (real driving simulator), different people (sex, age and build) will be carried out in the continuity work. Further work on several simulations taking into account other types of noise, which may interfere with the signal from the rib cage (impulsive noise, multi-path, etc.).

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