A Simple Parameter Estimation Method for Periodic Signals Applicable to Vital Sensing Using Doppler Sensors

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Abstract: A Doppler sensor enables us to detect the movement of objects. It transmits an electro-magnetic wave and receives signals yielded by the reflection at the objects so that we can detect the movement of the objects by measuring the frequency deviation between the transmitted- and the received signals. Recently, it is also drawing attention as a tool of non-contact vital sensing such as heartbeats and breathing. This is particularly interesting as a means for monitoring of patients in hospitals or residents in nursing homes in order to make such facilities more efficient. In this paper, aiming at such application, we propose a new very simple signal processing scheme in order to estimate (1) the number of signals, (2) the period of each signal, and (3) the fundamental waveform. It is also emphasized that the estimations (1)–(3) are available for two signals. The performance is verified through computer simulations.

Key Words: Doppler sensor, parameter estimation, vital sensing, monitoring of patients, car safety.

1. Introduction

Non-contact vital sensing is the measurement of vital data such as heartbeats and breathing without putting sensors on the body. It is expected that the non-contact vital sensing enables us to make our daily life more secure and efficient [1].

As an application, we can think about hospitals and nursing homes for monitoring the status of patients or residents. The non-contact vital sensing is expected to drastically contribute to improve the efficiency of the operation and the management of these facilities.

A Doppler sensor is a device which is applicable to the non-contact vital sensing. As illustrated in Fig. 1, it transmits an electro-magnetic wave and receives its reflected version yielded at bodies so that the Doppler sensor outputs the frequency deviation between the transmitted- and the received waves. Since this frequency deviation is caused by the movement of the body surface, we can estimate the heartbeats and breathing through digital signal processing, using the samples of the receiver output obtained by the analog-to-digital converter (ADC).

In addition, if we can measure two persons using one Doppler sensor as illustrated in Fig. 2, it is possible to reduce the number of the sensors to be installed in hospitals where a number of measurement must be conducted in parallel.

From the signal processing perspective, this is attributed to the parameter estimation of periodic signals. Although it is a classic problem in this field, it is still not easy to conduct the parameter estimation for a signal containing multiple periodic signals overlapping on the frequency axis. Needless to say, the signal processing must be robust against noise, since the transmitted signal must be sufficiently weak in order to avoid any harmful effect for human bodies, and the received signals are mitigated through not only propagation but also by clothing.

Furthermore the signal processing is required to be simple in order to reduce hardware scale as much as possible so that we can reduce the cost of manufacturing.

Conventional methods [2]–[4] never deals with multiple periodic signals. The literature [2] is for measuring the wrist pulse, so there is no need to distinguish multiple periodic signals. The method in [3] targets the extraction of fetal heart rate in a pregnant woman, and it does not discuss the estimation of multiple periodic signals. Looking at other fields except the vital sensing, [4] proposes a new method for the period estimation of a pseudo-random code employed in spread spectrum communication systems. Again, this paper does not discuss how the proposed method estimates if there are multiple periodic signals. Although this is not discussed, we can imagine that this

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method is available for multiple uncorrelated signals. However, it would not be available for highly correlated multiple signals. Although the methods presented in [5] and [6] are capable to cope with the multiple signals, they cannot estimate the fundamental waveform at the same time. Similarly, the several methods compared in [7] also do not estimate the fundamental waveform. A more advanced version in [8] was proposed to conduct the parameter estimation for the two bodies. This method also allows us to estimate the fundamental waveforms. However, this method requires multiple antennas at the receiver and we obtain the multiple reflected signals from the identical AOA. Of course, it costs a lot of computational complexity and hardware resources due to the usage of multiple antennas.

In this paper, we propose a very simple method for the parameter estimation of multiple periodic signals overlapping on the frequency axis. The proposed method is capable to estimate the parameters such as (1) the number of signals (NOS), (2) the period for each of the periodic signals and (3) the fundamental waveform for each of the periodic signals. It does not require multiple antennas, and it is robust under noisy environment. In addition, the proposed method is realized by the addition only, so there is no multiplication. This is advantageous for the hardware implementation using the application specific integrated circuit or field programmable gate array in order to reduce the hardware scale. Although we implied the principle of the idea with a few numerical examples in [9], this paper provides a precise description and extensive performance verifications of the proposed method.

The following sections are organized as follows: Based on the mathematical formulations of signals given in Section 2, Section 3 provides in-depth explanations of the proposed method. Section 4 verifies the performance of the proposed method through computer simulations. Finally, Section 5 concludes this paper.

2. Formulations of Signals

Figure 3 illustrates the vital sensing using a Doppler sensor. The transmitter sends \( x(t) \) which will be reflected by human bodies, yielding the multiple reflected signals \( s_1(t) \) and \( s_2(t) \).

The receiver outputs \( x(t) \) containing \( s_1(t), s_2(t) \) and noise \( \eta(t) \). In reality, the receiver outputs \( x(t) \) is the voltage proportional to the frequency deviation caused by the Doppler effect. Finally the analog-to-digital converter (ADC) performed the sampling and we obtain \( x[k] \). The received signal \( x(t) \) is sampled as follows:

\[
x[k] = x(kT_S),
\]

where \( T_S \) denotes the sample interval while \( k \) is an integer as a time index. Hereafter, the samples of the signals formulated above is denoted by replacing \( t \) with \( k \). So \( x[k] \) is expressed as follows:

\[
x[k] = \sum_{n=0}^{N-1} s_n[k - \tau_n] + \sqrt{\frac{P_S}{2}} \eta[k],
\]

where \( N \) is NOS. Let the subscript \( n \) correspond to the \( n \)-th signal. An unknown time offset is denoted by \( \tau_n \) while \( P_S \) and \( \eta[k] \) are the noise power and the unit-power complex noise, respectively. The complex noise \( \eta[k] \) is defined as follows:

\[
\eta[k] = \eta_\Re[k] + j\eta_\Im[k],
\]

where \( \eta_\Re[k] \) and \( \eta_\Im[k] \) are independent- and identically-distributed random variables following \( N(0, 1) \).

In addition, the signal \( s_n[k] \) is defined as

\[
s_n[k] = e^{j\phi_n} \sum_{m=0}^{M-1} \sqrt{P_n^{(n)}} \phi_n[k - mT_n].
\]

where \( P_n^{(n)} \) denotes the signal power of the \( n \)-th signal. The unit-power fundamental waveform is given by \( \phi_n[k] \) of which the period is defined by \( T_n \). Finally, \( M \) is the number of the repetition of the fundamental waveform \( \phi_n[k] \) contained in \( s_n[k] \) while \( \phi_n[k] \) denotes the initial phase of \( s_n[k] \).

In this paper, we propose a simple method to estimate the fundamental waveforms \( \phi_n[k] \), the NOS \( N \) and the periods of each fundamental waveforms \( T_n \). It is suitable for the vital sensing using the Doppler sensor due to its simplicity and sufficient performance.

3. Proposed Method

This section provides in-depth explanations of the proposed method. Prior to detailed explanations, the basic idea of the proposed method is intuitively explained in the next section in order to facilitate understanding [9]. Based on the understanding, details of the configuration will be provided as well as the procedure of the parameter estimation of the proposed method.

3.1 Basic Idea

The core of the idea is simple. Let us compare Fig. 4 with Fig. 5. In both figures, a periodic sample sequence is fed into a serial-to-parallel converter (SPC). The period of the sample sequence is 8 samples. Now, focusing on Fig. 4, the number of the output ports of the SPC is identical to the period of the input sample sequence, 8. In this case, we can obviously imagine that the outputs of the SPC is always the same over the time axis \( g \). Therefore it is expected that the accumulation of the SPC outputs grows large.

In contrast, let us focus on Fig. 5. The point is that the number of the output ports of the SPC is 7, which is not equal to the period of the input sequence. In this case, we can imagine that the output of the SPC is never identical. Thus the accumulation of the SPC outputs is not likely to grow as large as we saw in Fig. 4. The proposed method exploits this property for the estimation of \( \phi_n[k], N \) and \( T_n \).
The figures we saw above imply the following estimation method: Let us put multiple SPCs in parallel. The number of the output ports are different. Then input in parallel the sample sequence of the signal to those SPCs and accumulate the outputs at each of the SPCs. By comparing the absolute value of the accumulated SPC outputs among all of the SPCs, we must be able to identify one SPC that yields the maximum absolute value of the accumulated SPC outputs. The number of the output ports of the identified SPC is the period. In addition, the accumulated output of the identified SPC is analogous to the fundamental waveform of the periodic signal. This is the basic idea of the proposed method.

The following section provides a detailed description of the configuration and the procedure of the proposed method.

3.2 Configuration

Figure 6 shows the configuration of the proposed method. The samples \( x[k] \) are copied and are fed into the SPCs. In this figure, multiple SPCs are placed. These are identified by the number \( \#1 \) to \( \#V \). Let us call this number as SPC ID. The number of the SPC output ports is the minimum at SPC\#1, equipped with \( U_{\text{min}} \) ports. The adjacent SPC \#2 is equipped with \( (U_{\text{min}} + 1) \) ports. Likewise, the number of the output ports is incremented by 1 till the SPC \#V equipped with \( U_{\text{max}} \) ports as the maximum. Therefore, the relationship between the SPC ID \( v (= 1, \ldots, V) \) and the number of the output ports \( u (= U_{\text{min}}, \ldots, U_{\text{max}}) \) is formulated as follows:

\[
  u = \Lambda(v),
\]

The g-th \( (g = 0, \ldots, G-1) \) output of the SPC \#v is expressed by the vector \( x_v[g] \) of size as follows:

\[
  x_v[g] = \begin{bmatrix}
  x_1^{(v)}(g) \\
  x_2^{(v)}(g) \\
  \vdots \\
  x_u^{(v)}(g)
\end{bmatrix}^T,
\]

The \( g \)-th \( (g = 0, \ldots, G-1) \) output of the SPC \#v is expressed by the vector \( x_v[g] \) of size as follows:

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  \vdots \\
  x_u^{(v)}(g)
\end{bmatrix}^T,
\]

Then the SPC output is accumulated as follows:

\[
  \hat{x}_v = \sum_{g=0}^{G-1} x_v[g].
\]

3.3 Procedure

Recall that Figs. 4 and 5 explained the SPC outputs and their accumulations. Based on the configuration above, the procedure of the parameter estimation is listed in the following.

**Proc. 1** Identify the maximum absolute value of the accumulated SPC outputs at each of the SPCs. This identification is formulated as follows: Let us denote the entities of \( \hat{x}_v \) as

\[
  \hat{x}_v = \left[ \hat{x}_1^{(v)}, \hat{x}_2^{(v)}, \ldots, \hat{x}_u^{(v)} \right]^T.
\]

Then, detect the following for all of the SPCs, \( \#1, \ldots, \#V \).

\[
  \bar{x}_v = \max_{w=1,\ldots,V} |\hat{x}_w^{(v)}|.
\]

**Proc. 2** Sort \( \bar{x}_v \) \( (v = 1, \ldots, V) \) in the decreasing order and put them into the following vector.

\[
  \bar{x} = \left[ \bar{x}_{D(1)} \bar{x}_{D(2)} \ldots \bar{x}_{D(V)} \right]^T,
\]

where the function \( D(v) \) is to convert \( v \) to the decreasing order. It should be noted that \( \bar{x} \) is normalized by the maximum value \( \bar{x}_{D(1)} \).

**Proc. 3** Set \( \text{counter} = 1 \).
Check if $\bar{x}_{\text{counter}}$ is larger than a threshold $\delta$. If YES, go to Proc. 5. Otherwise, go to Proc. 6.

Proc. 5 The period of the fundamental waveform is estimated as $\Lambda(D(\text{counter}))T_S$ while the fundamental waveform is $\hat{x}_{D(\text{counter})}$. In addition, increment counter by 1 and go back to Proc. 4.

Proc. 6 Finish. The NOS is estimated as $N = \text{counter} - 1$.

Numerical examples of the above-mentioned simple procedure is provided in the following section.

4. Computer Simulations

4.1 Numerical Examples

This section provides numerical examples of the parameter estimation, i.e., the estimation of the fundamental waveforms, NOS and its periods for the multiple signals contained in the observed noisy signal. Table 1 lists conditions. We generate two fundamental waveforms with different period settings by using a roll-off filter.

The signal-to-noise power ratio (SNR) is set at $-10$ dB. The periods of the two fundamental waveforms $\phi_1[k]$ and $\phi_2[k]$ are set at $T_1 = 31$ samples and $T_2 = 32$ samples as depicted in Fig. 7. Actually $\phi_2[k]$ is formed by expanding the tail of $\phi_1[k]$ appending one sample of 0 as depicted in the figure. In addition, $\phi_1[k]$ is the impulse response of the roll-off filter of which the roll-off factor is set at 0.5.

By setting the phase shift $\phi_1 = \pi/4$ and $\phi_2 = -\pi/4$, the fundamental waveforms are successively connected to form chains of the fundamental waveforms, as formulated in (4). Figure 8 shows the real- and imaginary-parts of $s_1[k]$ and $s_2[k]$. It is seen that $s_1[k]$ and $s_2[k]$ are quite similar even though the periods are just slightly different. It should be emphasized that these two signals are overlapping in the frequency domain. Therefore it is impossible to divide those two signals by filtering.

The received signal is as formulated in (2). Figure 9 shows the image of the waveform of the received signal. Obviously the two signals are completely buried by noise where the signal-to-noise power ratio is set at $-10$ dB.

Furthermore, we can estimate NOS using Fig. 10, showing the number of the output ports of the SPCs versus the $\bar{x}$ normalized by $\bar{x}_{D(1)}$. It is clearly seen that there are two large values at $u = 31$ and 32, enabling us to estimate the periods of the signals.

Finally, Figs. 11 and 12 show the estimated fundamental waveforms found at the SPCs equipped with 31 and 32 output ports. In order to evaluate the quality of the estimation, we measure the SNR $\Gamma_1$ and $\Gamma_2$ corresponding to the estimated fundamental waveforms $s_1(t)$, $s_2(t)$ by the following formula:

$$\Gamma_n = 10 \log_{10} \left( \frac{|\rho_{n}|^2}{1 - |\rho_{n}|^2} \right) \text{ dB}, \quad (12)$$

Table 1 Conditions.

| SNR (dB) | $M_1 = M_2 = 1000$ |
|---|---|
| The number of period | $\rho_1^1 = \rho_2^1 = 1$ |
| Fundamental waveforms | $\phi_1[k], \phi_2[k]$ |
| Impulsive response | roll-off filter |
| Phase | $\phi_1 = \pi/4, \phi_2 = -\pi/4$ |
| Period (sample) | $T_1 = 31, T_2 = 32$ |
| Time offset | $\tau_1 = \tau_2 = 0$ |
Fig. 10 The number of SPC outputs ports vs. the maximum absolute value of the accumulated SPC outputs.

Fig. 11 Estimated fundamental waveform of $s_1$.

Fig. 12 Estimated fundamental waveform of $s_2$.

where

$$\rho_1 = \frac{s_1^H s_1}{s_1^H \hat{x}_3} \hat{x}_3^H s_1$$  \hspace{1cm} (13)

$$\rho_2 = \frac{s_2^H s_2}{s_2^H \hat{x}_3} \hat{x}_3^H s_2$$  \hspace{1cm} (14)

In the equations above, $s_1$ and $s_2$ are defined as follows:

$$s_1 = \begin{bmatrix} s_1[0] & \cdots & s_1[30] \end{bmatrix}^T$$  \hspace{1cm} (15)

$$s_2 = \begin{bmatrix} s_2[0] & \cdots & s_2[31] \end{bmatrix}^T$$  \hspace{1cm} (16)

Through the calculations above, we obtain $\Gamma_1 = 17.0$ dB and $\Gamma_2 = 15.9$ dB. This quality can be improved by observing long time. In fact, we obtain $\Gamma_1 = 26.0$ dB and $\Gamma_2 = 26.4$ dB by setting $M_1 = M_2 = 10000$ at Table 1.

4.2 Computational Complexity

This section evaluates the computational complexity of the proposed method. The core part of this method consists of the addition only. The complex addition is composed by two additions. In the configuration employed in the numerical example provided in the previous section, the number of the addition is calculated as follows: Remember that the period of the longer fundamental waveform $s_2$ is set at 32 while the number of the period is set as $M_1 = M_2 = 1000$, and thus the number of the input samples $K$ is 32000. Let us calculate the total number of the additions performed in all of the SPCs in which the number of output port $u$ varies from 20 to 40. It is formulated as follows:

$$\Upsilon_{\text{proposed}} = 2 \sum_{u=20}^{40} \left\lceil \frac{32000}{u} \right\rceil = 46788,$$  \hspace{1cm} (17)

where $\lceil x \rceil$ indicates the minimum integer greater than or equal to $x$.

In order to evaluate $\Upsilon_{\text{proposed}}$, it is compared with the fast Fourier transform (FFT) as a typical means for signal analysis. As it is well-known, FFT consists of $K_1 \log_2 K_1$ complex multiplications and the identical number of complex additions where $K_1$ denotes the number of samples that are fed into FFT.

The complex multiplication includes 4 multiplications. Each of the multiplications is implemented by a barrel shifter and an adder, and realized by a repeat of the additions [10]. In the case of a 12-bit multiplication, 12 additions are required as the maximum. As the minimum, only one addition is enough. Now, for the evaluation, it is assumed that six additions are required for a multiplication. Therefore, in total, one complex multiplication needs $6 \times 4 = 24$ of additions.

Although it is not easy to consider a fair comparison between the proposed method and FFT, it is assumed that $K_1 = 32 (= 2^5)$. The reason of this setting is that $2^5$ is a power of 2 and less than 40 that corresponds to the setting of $U_{\text{max}} = 40$, the maximum number of SPC output ports. It means that this assumption is set so as to be favorable for FFT.

In this case, FFT is repeatedly conducted $32000/32 = 1000$ times. Eventually, the number of additions necessary for the realization of the complex multiplications in FFT is counted as follows:

$$e_M = 1000 \times 24 \times 32 \log_2 32 = 3840000.$$  \hspace{1cm} (18)
The number of additions necessary for the realization of the complex additions in FFT is counted as follows:

\[ \varepsilon_A = 1000 \times 2 \times 32 \log_2 32 = 320000. \]  

(19)

Hence the total number of the additions required by FFT is obtained as follows:

\[ \Upsilon_{\text{FFT}} = \varepsilon_M + \varepsilon_A = 4160000. \]  

(20)

Since \( \Upsilon_{\text{Proposed}} / \Upsilon_{\text{FFT}} \approx 0.011 \), it is possible to say that the computational complexity of the proposed method is remarkably lower than that of FFT. It should be noted that this is obtained based on the favorable assumption for FFT.

4.3 Statistical Evaluations

In this section, the performance of the proposed method is statistically verified through computer simulations. The procedure is given below.

**START**

**Step 1** Set \( \text{successCounter} = 0 \) and \( \text{simCounter} = 1 \).

**Step 2** Generate \( \phi_1[k] \), the sample sequence of \((k = 0, \ldots, 30)\) randomly following the Gaussian distribution. The power is normalized at 1.

**Step 3** Generate \( \phi_2[k] \) randomly following the Gaussian distribution, independently from \( \phi_1[k] \). Then, appending \( \phi_2[31] = 0 \) to extend the period for 1 sample. The power is normalized at 1.

**Step 4** The signals and noise are combined as (2) and (4) by setting \( P_S^{(1)} = P_S^{(2)} = 1 \) and the phases \( \varphi_1 \) and \( \varphi_2 \) are randomly decided following the uniform distribution on \([0, 2\pi]\).

**Step 5** Perform Proc. 1 to 6 in Section 3.3.

**Step 6** If NOS and the periods of the fundamental waveforms are correctly estimated, i.e., NOS is 2 and the periods are 31 and 32, increment \( \text{successCounter} \) by 1 and calculate the SNR of the estimated fundamental waveform by (12). Note that the SNR is calculated only if the NOS and the periods are correctly estimated.

**Step 7** Increment \( \text{simCounter} \) by 1.

**FINISH** If \( \text{simCounter} = 1001 \), finish. Otherwise, go to Step 2.

Other settings which are not found in the steps above are identical to those listed in Table 1.

Figure 13 shows the input SNR \( P_S^{(1)} / P_\eta = P_S^{(2)} / P_\eta \) versus the success ratio of the estimation \( \text{successCounter} / 1000 \) by varying \( \delta \) as 0.6, 0.65 and 0.7. It is seen that the higher value of \( \delta \) achieves higher success at SNR lower than \(-15\) dB. However, the lower value of \( \delta \) achieves better success ratio with high SNR.

Figures 14 and 15 shows the input SNR versus the SNR of the estimated fundamental waveforms \( \phi_1[k] \) and \( \phi_2[k] \), respectively. Recall that the output SNR is calculated only if the NOS and the period of each signal are correctly estimated.

**5. Conclusion**

Aiming at non-contact vital sensing with Doppler sensors, this paper proposed a simple parameter estimation method which is applicable to multiple periodic signals overlapping on the frequency axis. The proposed method estimates NOS, the period for each of the periodic signals and the fundamental
waveform for each of the periodic signals, with a single antenna. It is robust under low SNR environment, and advantageous for hardware implementations because it contains only additions, not multiplications. It should be also emphasized that the proposed method can cope with two incoming signals to conduct the parameter estimation for each of them.

Future projects include its hardware implementation and performance verifications through experiments.

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