Improved heartbeat detection by exploiting temporal phase coherency in FMCW radar

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ABSTRACT We propose a novel range-bin selection method, temporal phase coherency (TPC), to improve the accuracy of heartbeat extraction by using the frequency-modulated continuous wave (FMCW) radar. The FMCW radar has a range-resolution, and the micro-displacement at each range bin can be analyzed by calculating the phase corresponding to the range. To extract accurate heartbeat signal, selecting the range bin is important. However, the heartbeat signal, whose displacement is minute, is hard to be detected. To select the range bin with accurate heartbeat signal, we quantified the unique characteristic of heartbeat, sinus rhythm, as TPC index. In experimental results, we evaluated the accuracy of extracted heart rates for various subjects and experimental situations. The results showed that the TPC can select the range bin with more accurate heartbeat compared to the conventional methods, indicating that the TPC would be useful for the FMCW radar based vital-sign monitoring.

INDEX TERMS FMCW radar, vital monitoring, heartbeat, range-bin selection, temporal phase coherency

I. INTRODUCTION

RADAR, which can operate continuously without users’ perception and cables, has been used for vital-sign (respiration and heartbeat) monitoring [1]–[5]. Vital signs are basic physiological indicators, that can be used to assess one’s medical diagnosis or fitness. In particular, the heartbeat, which is directly associated with autonomous nervous system functions and cardiovascular health, can provide important prognostic information for mental and physical diseases [6]–[9]. Various healthcare applications using radar have been developed, such as sleep monitoring [10]–[14], driver monitoring [15]–[18], infant monitoring [19]–[21], and monitoring of contaminated or burned victims [22], [23]. In particular, frequency-modulated continuous wave (FMCW) radar, which has range resolution, can localize the target as well as monitor the vital signs [24]–[26]. This property enables the FMCW radar to separate targets from clutters [25], [26] and perform multi-target monitoring [27]–[29]. In addition, the FMCW radar has the advantages of small size, low price, and low energy consumption [30], [31]. Therefore, the FMCW radar has been actively used for vital-sign monitoring [32]–[37].

The FMCW radar measures vital-sign signals by the range [24]–[26]. The FMCW radar contains information about the range as its frequency, and the displacements caused by vital signs in each range are reflected in the magnitude and phase of the corresponding spectral component. Because vital-sign signals exist in a specific range corresponding to body parts such as the thorax for respiration, and the artery in the neck for heartbeat, selecting the range is necessary to extract vital-sign information [33]–[36], [38], [39]. Heartbeat, for which the displacement is smaller than that for respiration, is vulnerable to artifacts and harmonics of respiration [40], [41], which makes it difficult to select the range with a heartbeat signal. Conventional methods select the range bin using the coherency between phases in different range bins [33], the coherency between magnitude and phase [32], [34], extent of magnitude [35], fluctuation of phase [36], or the phase average [37]. However, conventional methods do not consider the characteristics of the heartbeat
to select the range bin.

In this paper, a range-bin selection method is proposed utilizing the characteristic of heartbeat, sinus rhythm. The sinus rhythm is a regular and repetitive beats of heart, which occurs by electrical excitation initiated at the sinoatrial node propagating to the atria, atrioventricular node, and ventricle walls in order, which is repeated 60-100 times per minute [42]. The temporal phase coherency (TPC) index was devised to quantify the sinus rhythm in each range bin. Amplitude normalization [43], [44] was applied to exclude the effects of amplitude and to maintain a repetitive cycle in the signal. Then, the regularity and repetitiveness of the signal was quantified as the TPC index by measuring the coherency between the signal and the signal temporally shifted by the average period. The range bin with the maximum TPC index was selected for the heartbeat-signal extraction. Experimental results demonstrated that the TPC index is an effective indicator for detecting the range bin with a heartbeat signal, and the heart rates extracted by the TPC index are more accurate than those obtained by conventional methods.

II. METHODS

A. FMCW Radar Signal

The FMCW radar repeatedly transmits a linearly frequency-modulated radio wave, and receives the wave returned from the target. After the dechirping process, which mixes the transmitted and received radio waves with low-pass filtering, the beat signal, \( x(t, n) \) is calculated and modeled as

\[
x(t, n) = \sum_r M(t, r) \cdot \cos (2\pi \cdot f_r \cdot n + P(t, r)),
\]

where \( t \) is the scan-time index, \( n \) is the sample index in a chirp, \( r \) is the range, \( M(t, r) \) is the magnitude, \( f_r \) is the beat frequency, and \( P(t, r) \) is the phase.

By analyzing \( f_r, M(t, r) \), and \( P(t, r) \), the range and micro-displacement of the target can be identified [24]–[26]. The \( f_r \) is related to the range of the target as

\[
f_r = \frac{2BW}{c \cdot T_c \cdot F_s} \cdot r,
\]

where \( BW \) is bandwidth, \( c \) is speed of light, \( T_c \) is chirp duration, and \( F_s \) is sampling frequency.

The \( M(t, r) \) is the extent of the radio wave reflected from the target at \( r \). The \( P(t, r) \) is the time delay of the radio wave reflected from the target at \( r \), and modeled as in (3) [24]–[26], [32]–[34].

\[
P(t, r) = \frac{4\pi \cdot f_r}{c} \cdot r.
\]

The discrete Fourier transform is used to extract \( M(t, r) \) and \( P(t, r) \) as

\[
X(t, r_k) = \sum_{n=0}^{N-1} x(t, n) \cdot \exp \left( -j \cdot 2\pi \cdot k \cdot n \right),
\]

\[
M(t, r_k) = 2 \cdot \left| X(t, r_k) \right|,
\]

\[
P(t, r_k) = \angle X(t, r_k),
\]

where \( N \) is the number of samples in a chirp, and \( r_k = \frac{c}{2BW} \cdot k \) for \( k = 0, \ldots, N-1 \).

When a micro-displacement, \( \Delta(t) \), exists at \( r_k \), the \( \Delta(t) \) is reflected in \( P(t, r_k) \) as

\[
P(t, r_k) = \frac{4\pi \cdot f_r}{c} \cdot (r_k + \Delta(t)).
\]

Therefore, \( P(t, r_k) \) is linearly proportional to the \( \Delta(t) \), and the micro-displacement can be measured by analyzing \( P(t, r_k) \). In measuring the heartbeat signal, \( \Delta(t) \) is the displacement of the body surface caused by the heartbeat.
B. HEARTBEAT-SIGNAL MEASUREMENT

In our experiment, as shown in Fig. 1a, the subjects were located 0.5 to 1.0 m from the radar, whose parameters were set as in Fig. 1b. Electrocardiography (ECG) electrodes (Laxtha Inc. Korea) were attached to both wrists and right ankle for the referenced heartbeat. The standard deviation (SD) of \( M(t,r) \), \( \sigma_M \) is used to detect a human target [45] as shown in Fig. 1c. The detected boundary of the target was approximately 0.5 to 1.0 m corresponding to the real distance.

Fig. 2 shows the heartbeat-band filtered \( P(t,r) \) in the boundary of the human target, and the referenced heartbeat signal. According to conventional studies [32]–[34], [39], heartbeat signals exist in specific range bins corresponding to the body part where the skin is thin, such as the neck. As shown in Fig. 2b, among the range bins, \( P(t,r) \) near \( r = 0.800 \, \text{m} \) shows a high correlation with the referenced heartbeat signal. Fig. 2c shows the extracted heartbeat signal in the range bins where correlation with reference was highest (\( r = 0.800 \, \text{m} \)) and lowest (\( r = 0.675 \, \text{m} \)). The peak points of \( P(t,r = 0.800 \, \text{m}) \) were matched with the referenced R-peaks in the ECG, but \( P(t,r = 0.675 \, \text{m}) \) was not associated with the reference. Because the heartbeat signal exists in certain range bins, selecting the range bin is important for accurate measurement of heartbeat signal.

C. TEMPORAL PHASE COHERENCY

To select a range bin containing accurate heartbeat signal, we utilized sinus rhythm, which is a repetitive and regular beats of heart. We quantified sinus rhythm of \( P(t,r) \) at each range bin using TPC index, and selected the range bin based on the index. TPC index is calculated as follows. First, amplitudes of \( P(t,r) \), \( A(t,r) \) in each range bin are calculated using Hilbert envelope, and \( P(t,r) \) is normalized as in (6), to reduce the effect of amplitude and maintain the repetitive rhythm in \( P(t,r) \).

\[
\hat{P}(t,r) = \frac{P(t,r)}{A(t,r)}, \tag{6}
\]

where \( A(t,r) = |P(t,r) + j \cdot H(P(t,r))| \), and \( H(\cdot) \) denotes Hilbert transform.

Then, the average period of \( \hat{P}(t,r) \) in each range bin, \( T(t,r) \), is calculated using zero-crossing detection [46] as

\[
T(t,r) = 2 \sum_{k=1}^{K-1} \tau_k \frac{1}{K-1}, \tag{7}
\]

where \( K \) is the number of detected zero-crossing points in \( \hat{P}(t,r) \) during \( t - t_0 \) to \( t \), \( \tau_k \) is the time interval between \( k^{th} \) and \( (k+1)^{th} \) zero-crossing points.

The TPC index is calculated by shifting the \( \hat{P}(t,r) \) at each range bin with \( T(t,r) \) and calculating the coherency between
\[ \hat{P}(t, r) \text{ and } \hat{P}(t - T, r) \text{ as in (8), quantifying the temporal regularity of } \hat{P}(t, r) \text{ with respect to } T(t, r). \]

\[ TPC(t, r) = \frac{\sum_{s=t-t_0+T}^{t} \hat{P}(s, r) \cdot \hat{P}(s - T, r)}{\sigma_{\hat{P}}(t, r) \cdot \sigma_{\hat{P}}(t - T, r)}, \tag{8} \]

where \( \sigma_{\hat{P}}(t, r) \) is the SD of \( \hat{P}(t, r) \) from \( t - t_0 + T \) to \( t \) and \( \sigma_{\hat{P}}(t - T, r) \) is the SD of \( \hat{P}(t, r) \) from \( t - t_0 \) to \( t - T \).

The range bin with the maximum TPC is selected as the target range for the heartbeat signal, \( r_h \), as

\[ r_h(t) = \arg \max_r TPC(t, r). \tag{9} \]

Fig. 3 depicts the calculation of TPC index for the range bins with and without heartbeat signal. For both range bins, the amplitude of \( P(t, r) \) was normalized and a repetitive pattern maintained in \( \hat{P}(t, r) \). For \( r = 0.800 \) m, where the heartbeat signal existed, sinus rhythm was observed, and the coherency between \( \hat{P}(t, r) \) and \( \hat{P}(t - T, r) \) was high. However, for \( r = 0.675 \) m, where the heartbeat signal did not exist, the coherency was low. Consequently, the TPC index was high for \( r = 0.800 \) m, and low for \( r = 0.675 \) m.

Fig. 4 shows the TPC applied to the four subjects. For all subjects, the \( r_h \) was the range bin, where the correlation between \( P(t, r) \) and reference was high. Moreover, the peak points of the heartbeat signals extracted from the \( r_h \) were matched with the R-peaks in the referenced ECG. Therefore, the TPC can be used as an indicator for the selection of the range bin with an accurate heartbeat signal.

III. RESULT

A. SUBJECTS

A total of 21 subjects (16 men and 5 women) were selected for the experiment. The heart rates of all the subjects were within the normal boundary, 50-100 beats per minute (BPM) [47]. The subjects took at least 5 min of rest before the measurement, and the recordings lasted for 2 min. During the recording, the subjects sat comfortably on a chair without intentional movements.

In addition, for a subject, 5 min of heart rates before and after 20 min of light jogging were recorded to intentionally increase the heart rates. In addition, heart rates of a subject were measured by changing the distance from the radar from 0.4 to 1.4 m with a 0.2 m movement every 2 min. The recording was stopped during the movement.

All the subjects were informed about the entire process of the experiments in advance, and consented to the recordings. Because this study uses collections of non-identifiable data and involves negligible risk, this study dis exempted from the ethical review.

B. COMPUTATIONAL IMPLEMENTATION

The simulation was performed using MATLAB R2021a (MathWorks Inc., USA). The built-in function, FFT, was used to calculate the \( X(t, r) \). Before applying the FFT, Hamming window was applied to \( x(t, n) \) for the reduction of spectral distortion. The boundary of the human target was detected using \( \sigma_M \) with the CFAR detection method [48]. \( P(t, r) \) was calculated from \( X(t, r) \) using the built-in angle and unwrap.
functions. The time window for $P(t,r)$, $t_0$ was set 15 s. The heartbeat-band filter ($0.8 - 1.7$ Hz) considering normal adults' heart rate ($50 - 100$ BPM) [47] was applied to $P(t,r)$ at each range bin. To calculate $A(t,r)$, the built-in function, envelope, was used. Then, the TPC index was calculated for each range bin, and heart rates were extracted from $r_h(t)$, which had the maximum TPC value. For continuous monitoring, heart rates were calculated every second using zero-crossing detection.

Conventional range-bin selection methods were implemented as follows.

The method in [33] selects the range bin utilizing the coherency between the phases in different range bins as

$$r_h(t) = \arg \max_r \sum_{s=t-t_0}^t P(s,r) \cdot P(s',r') \cdot \frac{\sigma_P(r)}{\sigma_P(r')}$$

(10)

where $\sigma_P(r)$ is SD of $P(t,r)$.

The method in [34] selects the range bin by exploiting the coherency between the magnitude and phase at each range bin as

$$r_h(t) = \arg \max_r \sum_{s=t-t_0}^t M(s,r) \cdot P(s,r) \cdot \frac{\sigma_M(r)}{\sigma_P(r)}.$$  

(11)
Fig. 6 depicts scatter plots of the heart rates estimated by the proposed and conventional range-bin selection methods, compared with the referenced heart rates. The scatter plot of the proposed method showed a diagonal arrangement, meaning that the estimated heart rate was close to the reference.

Fig. 7 shows the Bland-Altman plot for the heart rates estimated by the proposed and conventional range-bin selection methods. The Bland-Altman plot shows the distribution of the difference between the estimated and referenced heart rate using the mean difference (MD) and SD of the difference. Table 1 lists the MD and 95% confidence interval (CI), which is MD±1.96·SD, of the Bland-Altman plot. The heart rates estimated by the proposed method had the lowest MD, -1.02 BPM with 95% confidence interval of -8.33/6.30 BPM.

Table 1. MD and confidence interval of the Bland-Altman plot.

| Method | MD    | 95% CI         |
|--------|-------|----------------|
| Proposed | -1.02 | -8.33 / 6.30   |
| [33]   | -1.13 | -7.77 / 5.62   |
| [34]   | -1.70 | -9.89 / 6.49   |
| [35]   | -3.13 | -13.61 / 7.35  |
| [36]   | -5.33 | -16.37 / 5.70  |
| [37]   | -4.14 | -15.43 / 7.15  |

In Table 2, the accuracy of the estimated heart rates in comparison with the reference was numerically evaluated using Pearson’s correlation coefficient $\rho$, mean error $\epsilon$, and
The $\rho$ measures linear correlation between two sets of values, $y$ and $z$ [49], as

$$\rho = \frac{\sum_i (y_i - \bar{y}) \cdot (z_i - \bar{z})}{\sigma_y \cdot \sigma_z},$$

where $\bar{y}$ and $\bar{z}$ are the mean, and $\sigma_y$ and $\sigma_z$ are the SD of $y$ and $z$.

The $\epsilon$ measures averaged absolute difference between two sets of values, as

$$\epsilon = \frac{1}{L} \sum_{i=1}^{L} |y_i - z_i|,$$  

where $L$ is the total number of elements in $y$ and $z$.

The $o$ measures the ratio of elements whose error is within the threshold [33], [34], [37], as

$$o = \frac{100}{L} \sum_{i=1}^{L} I(|y_i - z_i| < thr),$$

where $I$ is the indicator function.
**FIGURE 8.** Heart-rate extraction before and after exercise. (a), and (b) TPC, $r_h$, and Extracted heart-rate before and after exercise.

**FIGURE 9.** Heart rates extracted by changing the location of a subject. (a) Target distance, (b) TPC and $r_h$, and (c) extracted heart-rates.
where \( I(\text{statement}) = \begin{cases} 1 & \text{if statement = true} \\ 0 & \text{if statement = false} \end{cases} \), and \( thr = 5 \) BPM.

The heart rates estimated by the proposed range-bin selection method had the highest \( \rho \) and \( \alpha \), and lowest \( \epsilon \), meaning that the proposed method selects the range bins with accurate heartbeat signal.

**TABLE 2.** Error analysis of the heart rates extracted by various range selection methods.

| Method      | \( \rho \text{ (p<0.005)} \) | \( \epsilon \) | \( \alpha \) |
|-------------|-------------------------------|----------------|-------------|
| Proposed    | 0.78                          | 3.61           | 83.9        |
| [33]        | 0.78                          | 4.07           | 76.7        |
| [34]        | 0.68                          | 5.52           | 67.7        |
| [35]        | 0.37                          | 9.51           | 37.6        |
| [36]        | 0.20                          | 12.74          | 23.9        |
| [37]        | 0.14                          | 11.47          | 28.8        |

**D. VERIFICATION OF HEART-RATE EXTRACTION**

To verify the heart-rate extraction of the proposed method, we measured heart rates using the proposed method with some variations in the experimental situations.

In Fig. 8, we intentionally increased a subject’s heart rate through exercise, and compared the heart rates before and after the exercise. TPC in Fig 8.a,b was high from \( r = 1 \) to 1.2 m, and \( r_h \) was selected near 1.1 m. The extracted heart-rates before the exercise were approximately 70-80 BPM, and the heart rates after the exercise were approximately 90-100 BPM, showing that the heart rates extracted by the TPC can reflect the increase in heart rates after the exercise.

In Fig. 9, we measured the heartbeat of a subject by varying the location of the subject as shown in Fig. 9a. In the experiment, we set the boundary of the human target as 0.2–1.8 m. As shown in Fig. 9b, as the subject moved away from the radar, the range bins with a high TPC index and selected \( r_h \) also moved away. As shown in Fig. 9c, though the location of the subject varied, the estimated heart-rates were associated with the referenced heart rates. The results showed that the extracted heart rates were accurate even with changes in the subject’s location.

**IV. DISCUSSION**

For the detection of the body part with accurate vital signs, the systems utilizing additional devices have been used, such as non-linear radar [50]–[53] and hybrid fmcw-interferometry radar [45], that use non-linear devices (tag) or two-types of radar. However, the proposed method did not use additional devices, and detected the range bin corresponding to the accurate heartbeat by using single FMCW radar and utilizing a signal processing method. The TPC, which quantified repetitive and regular rhythm of heartbeat, was proposed to separate the range-bin containing accurate heartbeat with other stationary clutters. The heartbeat extracted by the proposed method was more accurate than those detected by the conventional range selection methods. However, for some subjects, the estimated had an error compared with the reference due to the unknown artifacts assumed as body motion, or respiration harmonics.

For future works, the range-bin tracking logic [54], [55] or the cancellation of respiration harmonic [56] can be applied for the stabilization of the heartbeat extraction. Furthermore, the proposed method can be extended for various situations, such as through the wall or multi-target vital-sign monitoring.

**V. CONCLUSION**

The accuracy of the extracted heartbeat signal varied by the range selection methods. For the selection of the appropriate range bin, the SPC, that quantified the sinus rhythm in each range bins, was newly proposed. The heartbeat signals in the range bins with a high SPC value were highly correlated with the referenced heartbeat signals. In the experimental results, the extracted heart rates of 21 subjects were shown. Then, the accuracy of the extracted heart rates in comparison with the referenced heart rates were numerically evaluated. The heart rates extracted by the proposed method were more accurate than those extracted by the conventional methods. In addition, in the circumstance that the subject’s heartbeat increased, and the location of the subject varied, the extracted heart rates were accurate.

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