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Signal Phase Estimation for Measurement of Respiration Waveform Using a Microwave Doppler Sensor

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Abstract— **This paper proposes and compares five methods for phase estimation to measure slight change of chest movement with respiration using a dual type microwave Doppler sensor. A body direction to the sensor affects the performance of the respiration measurement, because microwave reflection is sensitive to the surface direction. The phase estimation from two sensor signals is the most important part to measure respiration. Thus, we developed new five methods for phase estimation. These methods were evaluated by calculating correlation coefficients between estimated waveforms and reference ones. The results demonstrated that the phase estimation based on least square method is the best for respiration measurement with respect to both waveform estimation accuracy and calculation time.**

I. INTRODUCTION

Recently, monitoring the elderly people in their houses is growing demand for aging society. Especially, continuous measurement of their physiological data is important to prevent sudden disease or accidents. Traditional wearable devices can capture these data robustly. However, the devices constrict their daily natural activities. Thus, the wearable devices are not suitable for measurement in daily environment. The new contactless devices are desired for monitoring system. A microwave Doppler sensor is promising for contactless measurement in daily environment. The microwave Doppler sensor can measure velocity of a target object without contact. The velocity is estimated from the Doppler shift between the transmitted microwave and the microwave reflected by the moving object. The sensor has two important features; 1) the microwave is transparent to common objects such as clothes and walls but is opaque to the human bodies and 2) the Doppler shift of the microwave is sensitive enough to measure small movement. These features enable contactless measurement of both respiration and heart rate from body surface vibration using a microwave Doppler sensor [1][2][3]. These researches were conducted under the limited measurement condition where a target person is located in the near front of the sensor and the person faces the sensor. The expansion of the target area to the daily environment is desired. Especially, for the system to monitor the elderly people, contactless measurement of their respiration overall a room is important to estimate their safety and sleeping state.

In general, velocity is calculated directly from frequencies of transmitted and reflected signals based on Doppler effects. However, this approach is not suitable for respiration measurement because a speed of the body movement with respiration is slow and the movement itself is very small. The other approach is estimation of signal phase in time domain instead of frequency. The phase is sensitive to the distance between a sensor and a target. Thus, the respiration is often measured based on signal phase. Some researchers [4][5] measured respiration from signal phase using the microwave Doppler sensor under the simple condition where signals are always captured at good S/N ratio. The condition does not require a special method for phase estimation. However, measurement in daily environment needs methods for stable phase estimation because signal strength changes according to a distance and a direction from a sensor to a target person and the change of signal strength decreases phase estimation performance [6]. In addition, another problem is that the previous researches capture only frequency of respiration. Measurement of the respiration waveform itself is also important to monitor the elderly people and detect their respiratory disease. Evaluation of the estimated respiration waveform is important. Therefore, our research aims are to propose new methods for phase estimation from the microwave Doppler sensor signal and to compare the methods based on quantitative evaluation of the estimated chest movement waveform with respiration.

II. METHODS FOR SIGNAL PHASE ESTIMATION

A. Signal Model of Dual Type Microwave Doppler Sensor

A dual type microwave Doppler sensor is used in this research. The sensor provides two outputs $V^{(1)}$ and $V^{(2)}$, whose phases are 90 degrees different from each other. The signals are represented as

$$V^{(1)} = A^{(1)} \sin(\frac{4\pi R}{\lambda} + \phi_0) + O^{(1)} + w_1 \quad (1)$$

$$V^{(2)} = A^{(2)} \sin(\frac{4\pi R}{\lambda} + \phi_0 + \phi_{0_{diff}}) + O^{(2)} + w_2 \quad (2)$$

Where $A^{(1)}$ and $A^{(2)}$ are the amplitudes of the signal, λ is the wave length, R is the distance between the sensor and a target, ϕ_0 is an initial phase, $\phi_{0_{diff}}$ is difference of two signal phases, $O^{(1)}$ and $O^{(2)}$ are DC offsets (in this paper, simply called 'offset'), and w_1 and w_2 are noise. The difference of two phases $\phi_{0_{diff}}$ is ideally 90 degree, but strict tuning of

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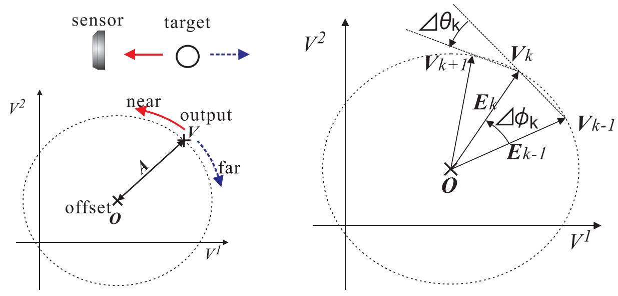

A) Lissajous curve and its relationship with target object movement

B) Vector representation of the signal and phase change on the Lissajour curve

Fig. 1. The Lissajous curve of the two signal outputs

the difference is difficult. From Eq. 1 and Eq. 2, the phase depends on the distance between the sensor and the target as

$$\Delta\phi = \frac{4\pi\Delta R}{\lambda} \tag{3}$$

This equation shows that difference of distance such as chest movement with respiration is estimated from the difference of signal phase. The Lissajous curve of the two signal outputs is plotted in Fig. 1-A) . Circle movement of the signal represents phase change. Distance change of half wave length is equivalent to one circle rotation (2π radian). The center of circle, which is called "offset" in this paper, changes according to various factors such as microwave reflection, environmental noises, electric power for sensor, and fluctuation of microwave transmitting amplitude. This change makes phase estimation difficult.

B. Phase Estimation based on Offset

To formulate phase change, a vector $\boldsymbol{E}$ from an offset point $\boldsymbol{O} = [O^{(1)}, O^{(2)}]^T$ to an output point $\boldsymbol{V} = [V^{(1)}, V^{(2)}]^T$ is introduced as Fig. 1-B). The phase ϕ is regarded as a rotation angle of the vector $\boldsymbol{E}$. The simple calculation of the phase ϕ is known [5] as

$$\phi = \arctan\left(\frac{V^{(1)} - O^{(1)}}{V^{(2)} - O^{(2)}}\right) \tag{4}$$

However, this direct calculation is unstable near ± 90 degree. To avoid this problem, the phase ϕ is calculated by integration of phase difference during small sampling period. The phase difference $\Delta\phi$ is directly estimated by angle difference between two vectors at time k and $k-1$ as

$$\Delta\phi_k = \arctan\left(\frac{\boldsymbol{E}_k \times \boldsymbol{E}_{k-1}}{\boldsymbol{E}_k \cdot \boldsymbol{E}_{k-1}}\right) \tag{5}$$

This approach needs direct offset estimation to calculate $\boldsymbol{E}_k$ and $\boldsymbol{E}_{k-1}$. The following four methods are prepared to measure this offset. To estimate offsets, all methods require some data samples. The sliding window is used to select needed data samples. Three parameters are needed for sliding window: size of window (N_{window}), sliding length in one step (N_{step}), and delay time from window start time to first sample time (N_{delay}) as Fig. 2

1) Mean of signals (MEAN): The mean of samples in a window approaches to an offset under the conditions where phase changes between 0 to 2π uniformly and offset is stable in a single window. The mean calculation is the simplest approach to estimate the offset.

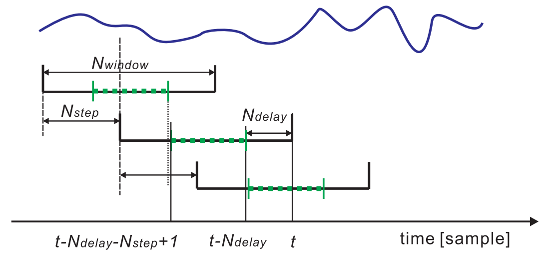

Fig. 2. The parameters for the window.

2) Least Squares (LS): In small duration, the data samples fit to a certain circle when the offset is fixed. The center of the circle is equivalent to the needed offset. The circle fitting problem is easily calculated using least squares method. The circle is defined with the radius A as

$$\|\boldsymbol{V}_i - \boldsymbol{O}\| = A \tag{6}$$

where i ($i = 0 \cdots n$) is index of the sample in a single window. Both the sides of the equation are squared as

$$\|\boldsymbol{V}_i\|^2 - 2\boldsymbol{V}_i^T\boldsymbol{O} + \|\boldsymbol{O}\|^2 = A^2 \tag{7}$$

A^2 and $\|\boldsymbol{O}\|^2$ are removed by taking the difference of Eq. 7 at the sample i and j to obtain the linear equation

$$2\left(\boldsymbol{V}_i - \boldsymbol{V}_j\right)^T \boldsymbol{O} = \|\boldsymbol{V}_i\|^2 - \|\boldsymbol{V}_j\|^2 \quad (i \neq j). \tag{8}$$

The offset $\boldsymbol{O}$ is estimated from Eq. 8 using least squares method. For the calculation, we define that i is fixed at the first sample index of the window and j is selected among indices of the other data samples.

3) Hough Transformation (HOUGH): In general, the data samples are distributed inhomogeneously. For example, when a target object does not move, the sensor captures the same values, which causes biased estimation. In addition, if the number of samples is small, even small noises distort estimation results. The popular approach to overcome these problems is discretization of output values. In this approach, the data area is divided into grid cells, and only occupied cells which contain data samples are used for calculation. In this research, the edge length of grid area is defined as

$$\begin{aligned} G_{width} = 2\max(&\max(V^{(1)}) - \min(V^{(1)}), \\ &\max(V^{(2)}) - \min(V^{(2)})) \end{aligned} \tag{9}$$

The centroid of the grid is the median of two signal output $V^{(1)}$ and $V^{(2)}$. The grid area is equally divided by the parameter N_{img}. The data samples in the window are voted into the grid cells. The voted grid cells are regarded as a kind of image data. Hough transform[7] is used to detect a circle from the grid.

4) Particle Filter (PF): The offset estimation from sequential window is regarded as a filtering problem. In this paper, we utilize a particle filter, which is a kind of Bayesian Filter [8]. The particle filter has less restriction of filter design. This feature provides robust estimation of the state. In this paper, we defined the state $\boldsymbol{x}$ with offset $\boldsymbol{O}$ and amplitude A as

$$\boldsymbol{x} = [O^{(1)}, O^{(2)}, A]^T \tag{10}$$

It is difficult to construct the transition model because offset movement is not predictable. Therefore, we define the transition model as

$$\boldsymbol{x}_k = \boldsymbol{x}_{k-1} + \Delta t \boldsymbol{w} \tag{11}$$

where $\boldsymbol{w}$ is Gaussian noise and Δt is time difference between k and $k-1$. The $\boldsymbol{w}$ is normal distribution with mean 0 and variances for the state items $\sigma_{O_1}^2$, $\sigma_{O_2}^2$ and σ_A^2. The observation model is calculated based on the assumption that the data samples fit a circle (Eq. 7) and the fitting error is modeled as a normal distribution with mean 0 and variance σ_{obs}^2.

$$p(\|\boldsymbol{V}_i - \boldsymbol{O}\|^2 - A^2 | \boldsymbol{x}) = \mathcal{N}(0, \sigma_{obs}^2) \tag{12}$$

The weight of j-th particle w^j is calculated from the above equation as

$$w^j = \prod_{i=1}^{N} p(\|\boldsymbol{V}_i - \boldsymbol{O}\|^2 - A^2 | \boldsymbol{x}^j) \tag{13}$$

where N is the number of samples in a window.

C. Direct Phase Estimation based on Vector Difference (DIFF)

The other method to estimate $\Delta\phi$ is calculating angle difference $\Delta\theta_k$ between the vector $\Delta\boldsymbol{E}$ as Fig. 1-B). As the figure illustrates, $\Delta\phi_{k+1}$ equals to $\Delta\theta_k$. $\Delta\boldsymbol{E}_k$ is calculated from $\boldsymbol{V}$ as

$$\begin{aligned} \Delta\boldsymbol{E}_k &= (\boldsymbol{E}_{k+1} + \boldsymbol{O}) - (\boldsymbol{E}_k + \boldsymbol{O}) && (14) \\ &= \boldsymbol{V}_{k+1} - \boldsymbol{V}_k && (15) \end{aligned}$$

This approach does not need to estimate offset as Eq. 15 does not contain $\boldsymbol{O}$. $\Delta\theta_k$ is easily calculated from $\Delta\boldsymbol{E}_k$ and $\Delta\boldsymbol{E}_{k-1}$ by replacing $\boldsymbol{E}_k$ to $\Delta\boldsymbol{E}_k$ in Eq. 5. The performance of this method depends on time difference between k and $k-1$, because short time difference data is unstable to estimate the angle $\Delta\theta_k$. To avoid this problem, the data for estimation is selected from the data sequence in the fixed interval N_{diff}.

III. Experiment for Method Comparison

We conducted experiments to compare the methods for phase detection. A subject stood in 1m front of a microwave Doppler sensor (NJR4261J, New Japan Radio Co., Ltd.). The subject changed his body direction in 45-degree step (the body faces just front of the sensor at 0 degree) as Fig. 3. The subject respired naturally in static posture. The sensor data were collected at 100 Hz. For analysis, sensor data were re-sampled at 10Hz by calculating mean of 10 samples after low-pass filtering (cut-off value 20 Hz). In one direction measurement, the data were recorded for 60 second. The middle part (40 sec.) of the recorded data was used for analysis. After estimation of signal phase using each method, the distance from initial position is calculated by integration of the phase difference $\Delta\phi$. As a reference, the chest movement with respiration was captured simultaneously using motion capture system (OptiTrack, NaturalPoint, Inc.) by 10 Hz. The three markers were attached on the thoracic wall in the front side of the subject. The wall

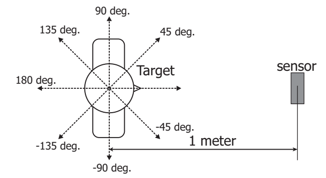

Fig. 3. Experiment condition

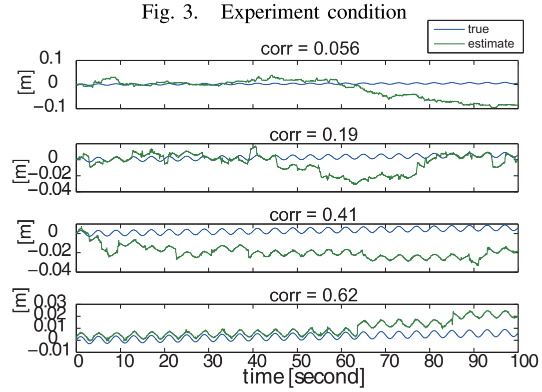

Fig. 4. The examples of true waves and estimated wave shapes with the evaluated value of its performance (correlation coefficient)

position was calculated as a mean of three marker positions. The performance is evaluated by calculating correlation coefficient between relative movement distance estimated from the sensor and measured by the motion capture system. From the preliminary experiment, we decided that cut-off value is 0.5. In other words, if the correlation coefficient is more than 0.5, the waveform is regarded as good expression of chest movement according to respiration. The typical waveforms are shown in Fig. 4. As the figure, the estimated waveform whose correlation coefficient is over 0.5 matches with the reference waveform well. In the experiments, all method parameters were optimized by the preliminary experiments.

Windows size affects performance of phase estimation based on offset. The performance changes were evaluated. In the experiment, window size N_{window} changed from 50 samples (0.5 sec.) to 1,500 samples (15 sec.) in 50-sample steps. N_{step} was fixed at 100. N_{delay} is defined as $N_{window}/2$. These parameters indicate that the offset values were estimated at 1 Hz in all conditions. The results are shown in Fig. 5. All methods achieved accurate respiration at the direction where the body faced the front of the sensor (0 degree, 45 degree 90 degree, and -45 degree). Fundamentally, the performance of estimation is expected to be symmetry at body direction (i.e., the result at 90 degree would be similar to that at -90 degree). However, the performances were asymmetry. The asymmetric body surface and slight difference of body direction might affect this difference of performance at symmetrical angles. The graph indicated that the methods except the particle filter needs 4-second window size to estimate the respiration accurately. This duration means that the methods require one cycle of respiration for window size. The particle filter shows stable estimation performance for change of window length. This method only uses the previous result to estimate the current offset, which may provide stable estimation and shorter window length.

On the other hand, the number of selected samples affects phase estimation performance based on vector difference.

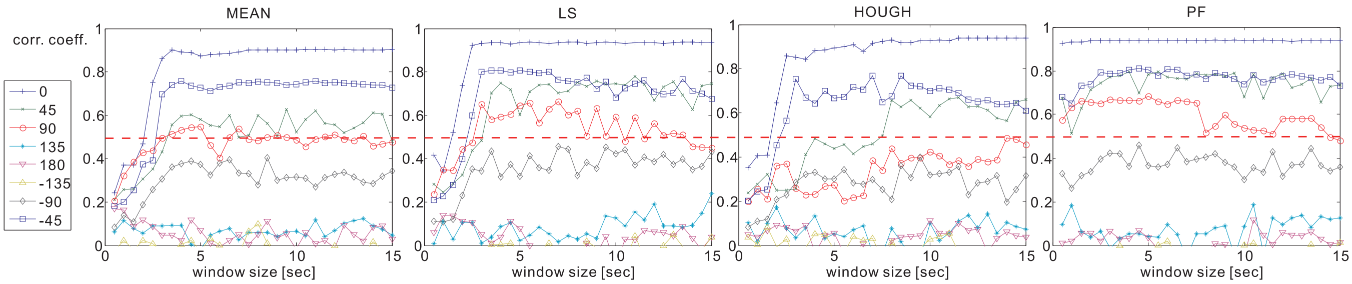

Fig. 5. The influence of the window size on the phase estimation

TABLE I

THE EVALUATION OF RESPIRATION MEASUREMENT FROM EIGHT DIFFERENT ANGLES BY EACH ESTIMATION METHOD

	0 deg.	45 deg.	90 deg.	135 deg.	180 deg.	-135 deg.	-90 deg.	-45 deg.	calc. time (sec.)
MEAN	0.91	0.63	0.55	0.12	0.17	0.10	0.40	0.76	< 1
LS	0.94	0.78	0.66	0.24	0.14	0.05	0.46	0.81	< 1
HOUGH	0.94	0.67	0.49	0.17	0.11	0.08	0.40	0.77	18
PF	0.94	0.80	0.68	0.19	0.12	0.02	0.46	0.81	168
DIFF	0.69	0.44	0.39	0.16	0.13	0.10	0.35	0.51	< 1

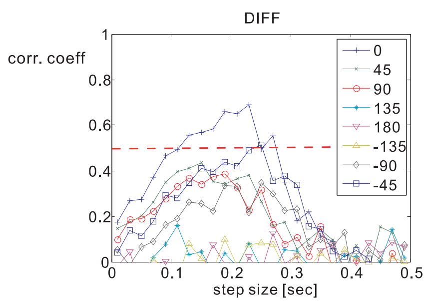

Fig. 6. The influence of the time step size on the phase estimation by DIFF

The relationship between the number of selected samples and the performance of respiration estimation was evaluated. The result when the interval between selected samples ($100/N_{diff}$) changes from 0.02 to 0.5 sec. is shown in Fig. 6. This method estimates respiration accurately only at 0-degree direction. The step size at the peak of the correlation coefficient was approx. 0.2 sec, which is corresponding to 10 sampling data. Since DIFF does not require estimation of extra-parameters such as offset, the performance was expected to be stable. However, the performance was worse than that of the phase estimation based on offset. Fundamentally, this method uses the second-order differential of the signals, which is weak for noise. This weakness might decrease the performance.

The summary of the maximum value of correlation coefficient at each condition is shown in Table I. Total calculation time is also shown in the right of the table. The time was measured when the method calculated the long data (the duration: 681.5 sec.) with N_{window} = 400 samples (40 sec.) and N_{step} = 100 samples (10 sec.) by laptop PC. This result indicates all methods can measure respiration accurately when a person faces front of the sensor (0 degree). Considering other angles (45 degree and -45 degree), the least squares method and the particle filter achieved high performance to estimate respiration. In addition, the result on calculation time suggests that the least squares method is promising for respiration with small computational cost.

IV. CONCLUSION

We proposed five methods for phase estimation to measure respiration using a dual type microwave Doppler sensor. These methods were compared at the various human directions and the parameters for the methods are explored by correlation coefficient of signal waveform with a reference data. Our experiments demonstrated that the best phase estimation method to measure respiration is least square method with 4-second window size. However, it is still difficult to estimate respiration accurately when the human body does not face the sensor. Our future work is to explore arrangement optimization of multiple sensors based on this result and developing new algorithm for integration of data from distributed sensors in order to realize contactless measurement of respiration whenever and wherever inhabitant is located.

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