Respiration Signal Extraction From Pulse Wave Collected by PVDF Sensor

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ABSTRACT The respiratory signal is a critical index of cardiopulmonary function. In this paper, we implement the polyvinylidene fluoride (PVDF) sensor to collect the data of pulse waves and reference respiration signals. The correlations between the major feature values and breaths are investigated and presented. As a result, several feature values exhibit relatively good correlations with reference respiratory amplitude. The improvements of Kalman Filter for the respiratory signals extracted from feature value variances are also introduced. Moreover, we display the comparisons with low-pass filtering, Wavelet filtering, and ensemble empirical mode decomposition (EEMD) method. Using the method of identifying error breaths, the error rate of the new method is about 4.146%. The new method is feasible for real-time applications at quiet state.

INDEX TERMS Pulse wave, respiratory signal, Kalman filter, PVDF sensor.

I. INTRODUCTION

As a critical physiological signal, respiratory signals, such as respiratory disorders, have been widely studied [1], [2]. In Chinese traditional medicine, the ratio of respiratory cycle to pulse cycle is seen as an important indicator of some diseases [3].

Except for directly getting respiratory information from nasal airflow or by sensor fixed on chest by belt, Reference [4] extracts cardio-respiratory signal from patient’s skin from video camera data for continuous non-contact vital sign monitoring. Reference [5] estimates respiration by performing the Fourier analysis on the time sequence of the optical flow vectors from a thoracoabdominal video. Reference [6] presents a wavelet-based algorithm for respiratory rate estimation from photoplethysmogram (PPG) signal; Reference [7] uses Doppler radar sensor for respiration estimation by ensemble empirical mode decomposition (EEMD) method. Reference [8] proposes a time domain autocorrelation model to process the signals from Doppler radar for rapid and stable estimation of the respiratory rate.

Several works have demonstrate the variation of pulse wave with respiration and use the characteristics of pulse wave for breathing signal extraction. For example, Reference [9] derives respiration signal from the width of pulse wave of PPG signal; Reference [10] discusses the respiration extraction based on pulse wave amplitude variation of PPG. The two works use only one type of feature value. Reference [11] extracts respiratory signals from electrocardiograph (ECG) and PPG, and discusses the application of Kalman Filter in data fusion of the two breathing signals for optimization, but the data acquisition is much complex.

As the Traditional Chinese Medicine (TCM) diagnosis is mainly based on pressure pulse signal, this paper discusses the feature value variation of radial pressure pulse wave with respiration. We will introduce the polyvinylidene fluoride (PVDF) sensor for data acquisition, and discuss the correlations between major feature values and respiration. This paper will discuss the feasibility of using Kalman filter on one or multiple feature values to optimize the extracted respiratory signals. The results are compared with other methods.

II. SIGNAL ACQUISITION AND PROCESSING

The paper uses PVDF piezoelectric film as the sensor for detecting pulse wave and the reference respiratory signal.
Piezoelectric film sensor is a kind of dynamic pressure sensor, which has high strength, broadband responses, soft material properties, good linearity, good time stability, and temperature stability [12]. The sensor is very thin, so it can be easily attached to the wrist surface and produce charge when it is stressed [13]. Fig. 1 is the equivalent circuit of charge amplifier which is used to convert the weak output charge of the PVDF sensor to voltage. $Q$ is the output charge of the PVDF film. $C_o$ and $C_i$ are equivalent capacitance of film and amplifier input [14]. The second stage amplifier could be the filtering-amplifying circuit, and the output voltage is the input of ADC. The MCU used in this system is STM32 [15], and the ADC in STM32 is 12 bit. The sampling rate is $f_N = 455\text{Hz}$. Butterworth low-pass filter and wavelet filter can be used for digital filtering.

The reference respiratory signals are collected by fixing the PVDF sensor on chest by strap. Fig. 2 shows the synchronous signals collected by 5 PVDF sensors placed near the second and third rib on the left chest from up to bottom. The distance between two adjacent sensors is about 1.6 cm. The dashed line is the reference respiratory signal from nasal airflow. The high value corresponds to exhalation, while the low value corresponds to inhalation. In this breathing process, there is no time gap between each exhalation and the inhalation after it. Because the respiratory signals detected by the PVDF sensor on chest are actually the detection of chest movement caused by breathing, the 5 synchronous signals show different characteristics due to the difference of skeletal and muscle structures at different positions.

Because the PVDF sensor is a type of dynamic pressure sensor and the reference respiratory signals are slowly changing, in Fig. 2, there are valley values in the inhalation parts after exhalation, which are caused by the discharge of amplifying circuits. Although the waveform shape is affected by discharge, the ascending and descending edges of the waveform can help distinguish the states of exhalation and inhalation. Compared with the dashed line, the amplitude of the respiratory signals collected by PVDF sensor on chest can directly provide relative respiratory intensity. The ascending and descending slopes are related to respiratory intensity or chest band pressure. This paper uses the signals that are similar to signal (2) in Fig. 2 as the reference respiratory signals by adjusting the collection position.

The synchronous radial pressure pulse waves are collected by fixing one sensor on the wrist by a clamp. If the arm is naturally placed on the desktop during data collection, the slight movement of arm during breathing could affect the clamp and cause fluctuations in the signal. Fig. 3 is used to observe the influence of arm movement. In order to have no pulse waves in the signal, the PVDF sensor is fixed on the...
back of the wrist by the clamp, and a thick sponge is used to block the pulse waves. Segment (b) is when the arm is naturally placed on the desktop, and segment (a) is when the elbow is on the desktop and the forearm is not. As shown, there are small fluctuations in segment (b), while there is almost no interference in segment (a). As the fluctuations may cause inaccuracies in the discussion of the correlation coefficients between pulse wave and respiratory amplitude, this paper will use the same posture as (a) for pulse signal acquisition.

Due to the high sensitivity of the PVDF sensor, respiratory signals collected on the left chest may contain small fluctuation signals, as shown in Fig. 4. These fluctuation signals may be related to the pumping of heart blood hitting the aortic root. Subfigure (b) is the synchronous collected waveform on chest under breath-holding state. The crosses of the radial artery pressure waveform in subfigure (a) mark some inflection points. The crosses in (b) are the positions that have a fixed time interval of 48 sampling points (about 0.1055 s) to the corresponding crosses in (a). As shown, these crosses are also near inflection points of the waveform in (b). Therefore, the correspondence between the inflection points of the two signals can be used to determine the pulse transit time (PTT) [16] of the pulse wave from signal acquisition position (b) to (a). The time value could be useful when the sampling rate is higher. In this paper, as the discussion is based on respiratory amplitude, the fluctuations are filtered out by wavelet filtering.

III. CORRELATION BETWEEN RESPIRATION AND PULSE WAVE FEATURES

As shown in Fig. 5, pulse wave consists of six major feature points \((b, c, d, e, f, \text{ and } g)\) [3], [17]. Point \(b'\) is the beginning of next pulse wave. Main feature values of pulse wave include time values, amplitude values, and area values of feature points, and they are generally calculated when the baseline between point \(b\) and \(b'\) is eliminated. For example, \(h_c\) is the amplitude of feature point \(c\) when the baseline is eliminated; \(t_e\) is the time interval of \(b\)-\(c\); \(t\) is the time length of the pulse wave; \(w\) is the time interval between the points of two thirds of the height \(h_c\); \(h_g - h_f\) is the amplitude difference between \(h_g\) and \(h_f\). Relative feature values can be computed from absolute feature values, such as \(H_f = h_f/h_c\) and \(T_f = t_f/t\).

In order to discuss the relation between feature values and respiration, Fig. 6 shows the scatterplot of major feature values and reference respiratory amplitudes of one subject. The radial artery pressure waveform and synchronous reference respiratory signal of the subject were collected in quiet state for 10 minutes. The respiratory amplitudes corresponding
to different feature values of a pulse wave are taken as the respiratory amplitude at its feature point $b$.

In Fig. 6, the red triangles are used to represent the pulse waves at low respiratory amplitude: hollow red ones are the pulse waves at respiratory baseline, and solid red ones are the pulse waves at respiratory troughs caused by discharge. The blue triangles are used to represent the pulse waves at higher respiratory amplitude: solid blue ones are the pulse waves in the descending segments of breath near respiratory troughs, and hollow blue ones are other pulse waves with higher respiratory amplitude than red triangles. So, in one respiratory cycle, the pulse waves marked by solid red triangle and solid blue triangle are adjacent. The relation between color and breathing amplitude is the same as the blue and red line in Fig. 2.

As shown, some feature values of this subject are correlated with respiratory amplitude. For example, in the subfigure of $t$, $t$ decreases with the increase of breath amplitude in the blue part. Because the number of pulse waves is large, the red part shows a broad value range. The yellow triangles are the pulse waves around one single exhalation, and it can be seen that the $t$ values of these triangles differ significantly. Compared with $t$, the value ranges of red and blue part of feature value $h_f - h_t$ are different, so $h_t - h_f$ has more obvious change characteristics with the respiratory amplitude. $t_c$ and $w$ have wide value ranges at different respiratory amplitude, so they cannot be used to distinguish breath state. The correlations between respiration and some relative time values, such as $T_c$ and $T_d$, are mainly based on the correlation of $t$.

Table 1 lists the significance ($\text{sig}$.) and Pearson correlation coefficients ($r$) of some major feature values of the subject. $\text{sig}.$ and $r$ are calculated based on all pulse waves in Fig. 6; $r'$ is calculated only based on blue triangles. According to the results for this subject, most feature values are significant ($\text{sig.} < 0.05$) and strongly or weakly correlated. Consistent with Fig. 6, $r$ of $h_f$ is larger than $r$ of $t$ as $h_f$ increases with the
increase of breath amplitude for both red and blue part. For this subject, $h_g - h_f$, $t - t_f$, and $t$ have more obvious correlation. Based on additional calculation, the correlation results are similar when PTT is considered by delaying breathing signal by the time length of PTT. Because pulse signal and respiratory signal are both periodic, the feature values are generally correlated.

### IV. RESPIRATORY SIGNAL EXTRACTION BASED ON FEATURE VALUE

Because feature point $d$ and $e$ do not exist in some pulse waves, the feature values related with feature point $b$, $c$, $f$, and $g$ are more general. Therefore, we mainly discuss the feature values that are not related to point $d$ and $e$, and are not relative values. Table. 2 gives the correlation coefficients of six subjects whose correlation coefficients are representative. Combined with Table. 1, feature value $h_g - h_f$, $A_s$, and time value $t_f$, $t_g$, $t$ show more stable correlation with respiration based on correlation coefficients.

Because the coefficients of $h_c$ and $t$ have different signs from $h_g - h_f$ in Table. 2, $-h_c$, $-t$, and $h_g - h_f$ are used in Fig. 7, which shows the cubic spline interpolation results of feature value sequence $h_c$, $h_g - h_f$, and $t$ of 3 subjects. The subject (1) and (2) in Fig. 7 are the subject (1) and (2) in Table.2. For the sake of observation, the amplitudes of some curves are subtracted by certain values. Subfigure (0) in Fig.7 shows the sequence of feature value $h_g - h_f$ and the reference breath signal of subject (1). The time position corresponding to each feature value in the sequence is taken as the position of feature point $b$ of the pulse wave.

For subject (2), although the correlation coefficient of $-h_c$ in Table 2 is small and even has the opposite sign with $-t$, the peak and trough positions of $-h_c$ curves in Fig. 7 (2) can correspond with the reference signal and $-t$ curve. $h_g - h_f$ of subject (2) has higher correlation coefficient than $-t$, but

**TABLE 1.** Correlation coefficients $r$, $r'$, and significance sig. of some feature values and respiratory amplitude in Fig. 6.

|       | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|-------|------|------|------|------|------|------|
| $h_c$ | -0.308 | -0.333 | 0.654 | -0.021 | -0.113 |
| $h_d$ | -0.413 | -0.483 | $t_d$ | 0.290 | -0.255 |
| $h_e$ | -0.441 | -0.505 | $t_e$ | 0.500 | -0.524 |
| $h_f$ | -0.503 | -0.580 | $t_f$ | -0.512 | -0.556 |
| $h_g$ | -0.225 | -0.298 | $t_g$ | 0.086 | -0.079 | -0.041 |

**TABLE 2.** Correlation coefficient $r$ of six representative subjects.

|        | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  |
|--------|------|------|------|------|------|------|
| $h_c$  | -0.437 | 0.114 | -0.149 | -0.377 | -0.327 | -0.326 |
| $h_f$  | -0.624 | 0.103 | -0.274 | -0.517 | -0.407 | -0.555 |
| $t_f$  | -0.870 | -0.425 | -0.670 | -0.557 | -0.705 | -0.543 |
| $h_g$  | 0.248 | 0.265 | -0.091 | -0.196 | -0.105 | -0.084 |
| $t_g$  | -0.613 | -0.171 | -0.342 | -0.300 | -0.480 | -0.510 |
| $h_g - h_f$ | 0.815 | 0.396 | 0.719 | 0.494 | 0.597 | 0.565 |
| $t - t_f$ | -0.131 | -0.277 | -0.496 | -0.269 | -0.314 | -0.358 |
| $A_s$  | -0.876 | -0.400 | -0.651 | -0.536 | -0.694 | -0.541 |
| $A$   | -0.641 | -0.192 | -0.591 | -0.401 | -0.490 | -0.364 |
the corresponding interpolation curve of $-t$ has better correspondence with the reference breath signal than $h_c - h_f$. For subject (1), the $-h_c$ curve has two maxima at one reference respiratory peak in Fig. 7. Therefore, the degree of correspondence between the interpolation curve and the reference respiration does not depend on the correlation coefficient.

Count of breaths can be calculated based on the amplitudes and positions of maxima in the discrete sequence of feature value. The problem, such as the lag of $-h_c$ in (2), does not affect the number of breaths, but it may affect the correlation coefficient value. For the problem that $-h_c$ of subject (1) has two maxima in a breath, we can determine that the two maxima correspond to the same respiratory peak by the fact that the minimum feature value between the two maxima is much larger than the baseline or the time interval between them is smaller than other breath intervals.

According to the results in Fig. 7, Table 2, and the work in References about pulse wave variability [9], [10], it is supposed that feature value $-t$ has relatively stable correlation with respiration, and it can be used for breath counting application. Because $-t$ is easy to compute, it can be used for real-time respiration extraction.

V. THE APPLICATION OF KALMAN FILTER

The calculation based on different feature value sequences may show different number of breaths. Such as $h_c - h_f$ and $-t$ in Fig. 7 (3), the number of breath counted by $h_c - h_f$ would be bigger than the number counted by $-t$. Moreover, the interpolation curve of single feature value may have large fluctuations. For getting better respiratory waveform, this paper discusses the use of Kalman Filter [18], [19] in respiratory extraction. In Kalman Filter, state vector $x$ and measurement vector $z$ satisfy the difference equation of discrete time process:

$$x(k) = Fx(k-1) + Bu(k)$$

$$z(k) = Hx(k) + v(k)$$

where $k - 1$ represents previous state and $k$ represents the present state. $Q$ is the covariance for process noise $w_k$; $R$ is the covariance for measurement noise $v_k$. $u$ is motion vector, $F$ is state transition matrix, $H$ is measurement parameter matrix, and $B$ is control matrix. The recursion formulas of Kalman filter are:

$$x(k|k-1) = Fx(k-1|k-1) + Bu(k)$$

$$P(k|k-1) = FP(k-1|k-1)F^T + Q$$

$$K_k(k) = P(k|k-1)H^T \left(HP(k|k-1)H^T + R \right)^{-1}$$

$$x(k|k) = x(k|k-1) + K_k(k) (z(k) - Hx(k|k-1))$$

$$P(k|k) = (I - K_k(k)H)P(k|k-1)$$

State vector $x(k|k)$ should be the respiratory amplitude which could be extracted from the $k$-th pulse wave, and measurement vector $z(k)$ at $k$ state is the feature value of the $k$-th pulse wave. $F = 1$ and motion vector $u(k)$ which represents stimulus is set to zero. Kalman filter is applied to the feature value sequence. The line $-t$ in Fig. 8 is the interpolation curve of the filtering result of feature value $-t$. For single feature value, $H = 1$. However, such as the $-t$ in Fig. 7 (1) and Fig. 8 (1), the interpolation curves obtained from the filtered sequences may not always be better than the results before filtering.

By assuming that all relevant parts of different feature values are due to respiration, multiple feature value sequences can be used for data fusion by Kalman filter, as the red and blue lines in Fig. 8. $H = [1; 1]$ or $H = [1; 1; 1; 1]$ when 2 or 4 feature values are used. $H$ can be modified to provide different weights to different feature values. Because different values have different ranges, for feature value sequence $F[n]$, $F'[n] = F[n] / (\max(F[n]) - \min(F[n]))$ is used in Kalman filter. So, the corresponding discrete sequences in Fig. 7 and Fig. 8 may have different values. The results
of “$h_g - h_f$, $-t$” and “$-h_c, -t_f, h_g - h_f, -t$” are better than the “$-t$” curve in Fig. 7 (1). But different from subfigure (1), the data fusion results of subfigure (3) are not better than the “$-t$” after filtering.

Therefore, for some pulse waves, the results of Kalman filter on one single feature value are better, but the data fusion results of multiple feature values would be better for other pulse waves. As it is assumed that all the relevant parts of different feature values are caused by respiration, data fusion result could be better than filtering result only when the feature value sequences used in Kalman filter are similar. For example, in subfigure (1), $h_g - h_f$ is more similar to $-t$ than $-h_c$, and the data fusion result “$h_g - h_f, -t$” is better; in subfigure (3), the data fusion result “$-h_c, -t$” is better than “$h_g - h_f, -t$” as $-h_c$ is more similar to $-t$, but because the degree of similarity is not as high as that in subfigure (1), it is not better than the $-t$ curve.

This paper presents a strategy for determining the similarity between two feature value sequences. The similarity is defined based on the similarity of maximum positions in sequences. $d(A, B)$ is denoted as the deviation of the maximum positions of feature value $A$ and $B$, and $n(A, B)$ is the approximate number of breaths calculated according to $A$ and $B$, then $D(A, B) = \frac{d(A, B)}{n(A, B)}$ is defined as the mean deviation value of each breath cycle. Sequence $B$ is taken as the standard, and the maximum positions of $A$ are compared with the maximum positions of $B$. As we suppose $-t$ has more stable correlation with respiration than other feature values and the value range of $-t$ is stable, this paper uses $-t$ as the standard sequence $B$. $A$ could be $-h_c$ or other feature values that show good correlation with the respiratory signal in Table 2.

Fig. 9 is the calculation process of $D(A, B)$ when $A$ is $-h_c$. As the number of pulses per breath is small, $A[i]$ is considered as maximum position when $A [i] > A [i - 1]$ and $A [i] > A [i + 1]$ is satisfied. The maximum positions of $A$ and $B$ are marked by “extremum” in Fig. 9. If $A[i]$ is maximum but $B [i - 1], B [i], and B [i + 1]$ are not, the $A[i]$ is assumed due to fluctuation (marked by “deviation 1” in (a)) and the deviation value $d(A, B)$ increases by 1.

When there is maximum in $B [i - 1], B [i], or B [i + 1], m_A$ and $m_B$ are used to represent the local mean feature value of $A [i]$ and $B [j]$. $m_A$ is calculated as the average value of the feature values, which are not maximum or minimum, near $A [i]$. Then there are three cases:

1. If $A[i] > m_A$ and $B[j] > m_B$, it is assumed that there is one breath and $n(A, B)$ should increase by 1; the $B[j]$ can no longer be paired with other values in $A[n]$, the corresponding $A[i]$ is denoted by “breath count” in subfigure (b);
2. If $A[i] < m_A$ and $B[j] < m_B$, it is assumed that there is no breath and the maxima are fluctuations. As $A$ and $B$ are still similar around, there is no deviation;
3. If ($A[i] - m_A$) ($B[j] - m_B$) < 0, it is assumed that there is deviation and $d(A, B)$ should increase by 1; in (b), the corresponding $A[i]$ is denoted by “deviation 2”.

In the calculation, it could happen that both $B[i - 1]$ and $B[i + 1]$ are maximum values. If the analysis of $A[n]$ is from small index to large index, we select $B[i - 1]$ first, but if $B[i - 1] > m_B$ is not satisfied, we would then select $B[i + 1]$ as $B[j]$ and check whether $B[i + 1] > m_B$ is satisfied.

$n(A, B)$ only represents the number of maxima that sequence $A$ and $B$ both have; it is not exactly equal to the number of breaths in the signal. Although $B$ is taken as $-t$ and $-t$ has good correlation with respiration, there may still be some fluctuations in the $-t$ sequence. As we do not suppose $A$ has maximum in each breath, if one maximum of $-t$ does not correspond to any maximum in $A$, we cannot tell whether this maximum of $-t$ corresponds to breathing or fluctuation. Therefore, this type of deviation is not included in the calculation of $d(A, B)$.

The $D(-h_c, -t)$ and $D(h_g - h_f, -t)$ of subject (1) (2) (3) in Fig. 8 are as shown in Table 3. The part used for calculation is the curve part in the Fig. 8. It can be seen that when $D(A, B)$ is small, the data fusion results of the two feature values in Fig. 8 are better than the filtering result of $-t$ by Kalman filter. When $D(A, B)$ is relatively large, such as $-t$ and $-h_c$ of (1), the data fusion result would not be better. According to the results, in the real application of this paper, if $D(A, B)$ of the sequence $A$ and $-t$ are smaller than 0.6, it is supposed that they are similar. If there are two feature values similar to $-t$, the data fusion could use three feature values, and so on. If there is no feature value similar to $-t$, we would apply Kalman filter on $-t$ and select the one with more obvious

![Fig. 9. The calculation process of $d(A, B)$ and $n(A, B)$ when feature value sequence $A$ is $-h_c$ and $B$ is $-t$. Amplitudes were changed.](image-url)
amplitude periodic change from the original $-t$ and filtered $-t$ as the respiratory result.

**VI. CONCLUSION**

This paper discusses the correlations between feature values of the radial pressure pulse wave and respiration. Feature values, such as $-t$ and $-h_c$, can be used for breath counting and getting the respiratory curve by interpolation. Kalman Filter can be used for data fusion of similar feature value sequences, or for filtering one single feature value, to improve the respiratory curve extracted from pulse wave.

Fig. 10 compares the breath extraction result with low-pass filtering method, wavelet filtering method, and EEMD method [20]. The feature values used in Kalman Filter are from $-h_c$, $-h_f$, $h_g$ $-h_f$, and $-t$ based on similarity. As shown, the curves of Kalman Filter and EEMD method show better correspondence with the reference breath signal. Compared with EEMD, the main advantages of the feature value method are that the computational complexity is much lower, and that it is suitable for determining respiratory signal in real-time application. However, unlike the EEMD method, the waveform obtained by EEMD method has no small fluctuations, while the interpolation curves of feature value sequences, such as $-h_c$ in Fig. 7 (1), may contain fluctuations and extra maximum values. And unlike the baselines of the EEMD results, which are always 0, the baselines of feature value sequences could fluctuate, such as the curve $-t$ in Fig. 8 (1). The accuracy of respiratory extraction based on feature values could be affected when the feature values are not accurate. Body movement would greatly influence the shape of pulse wave, so the feature value method is only applicable when the pulse waves are collected at quiet state. For other cases, the methods such as low-pass or wavelet filtering can be used.

Table 4 lists the number of error breaths in the curves extracted by feature value and EEMD from pulse wave signals without significant interference. The time lengths are about 2-5 minutes. EEMD parameters are $\text{Nstd} = 0.2$ and $\text{NE} = 200$. “total number of breaths” is from manual counting of reference breath signal. “error breaths” is the number of breaths that are not correctly extracted. The criterion for determining error breath is: if there is no maximum in a reference breath, or there are more than one maximum and it is hard to tell whether these maxima correspond to the same breath by their amplitudes or minimum amplitude between them, then it is considered that this breath is not extracted correctly. According to Table 4, the total error rate of feature value method is 25/603 = 4.146% and EEMD method is 53/603 = 8.789%. Therefore, the method based on feature value can be an efficient tool for extracting respiratory signal from pulse wave.

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