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Non-contact Breathing Rate Detection Based on Time of Flight Sensor*

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Abstract— **There are a growing number of methods to detect a person's breathing rate, but most techniques still either require contact with body skin or are usually uncomfortable to wear, too expensive and unfriendly for daily monitoring. The massive adoption of smartphones in recent years has created many opportunities to improve daily health monitoring. In this work, we demonstrated that off-the-shelf ToF lens on smartphones can capture a person's breathing rate while still. In addition, we proposed a method for extracting breathing rate from ToF signal and compared it with actual breathing rate obtained from temperature sensor. We evaluated the breathing rate accuracy of 6 people at rest, with a mean absolute error of 0.009Hz when considering different mean breathing rate conditions. Moreover, the mean absolute error percentage is 3.56% and the root mean squared percentage error is 6.64%, which is smaller than other methods of non-contact breathing rate detection in recent works.**

I. Introduction

Breathing rate (BR) is widely considered the indispensable vital sign in clinical practice, which can be an effectively predictor of potentially serious clinical events [1]. Thus, the monitoring of BR plays a pivotal role in health monitoring technology (e.g. elderly home care). However, conventional contact-based approaches to BR measurement are usually discommodious and may contribute to an imprecise outcome ascribing to some underlying effects (e.g. irritation effects of the nose clip and mouthpiece on nasal and oral mucosa) [2].

In recent works, many researchers study the methods of detecting non-contact breathing rate. The microwave radar measures the movement of human chest and back surfaces, which contains the information of breathing rate in the form of phase [3]. By analyzing the change rule of phase, it can achieve the purpose of measuring breathing rate. Surface displacement of 1.0-5.0mm due to respiration can be measured.

Hayashi T and others proposed using airborne ultrasound to measure breathing rate [4]. In their design, a loudspeaker emits an M-sequence modulated ultrasound to the human chest, and two microphones close to the loudspeaker receive the reflected echo, which is subsequently correlated with the transmitted M-sequence. The time of flight of the reflected echo represents the distance to the human chest.

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The visible light sensing is used in H.Abuella and S.Ekin's research [5]. After emitting a visible light signal to the human body, the signal will then be amplitude-modulated due to the periodic movements of human body. The modulated signal is subsequently reflected to the receiver, which extracts tiny periodic changes from it. With a contact-based device as a baseline, the accuracy of the system can be no less than 94%.

In this paper, we propose a non-contact breathing rate detection method based on a ToF sensor. The ToF sensor, a common component in smartphones, is used to measure the distance between the user's chest and itself fast and precisely. From the received data we can extract breathing rates to estimate BR preliminarily. Then, with the help of a model trained by the comparison between the labelled and estimated BR data, a more accurate result can be obtained finally.

II. Methods

A. System Model

In this work we explore using a Time of Flight (ToF) sensor to capture the continuous distance of chest motion from a person. This method is carried out at a relatively long distance, as far as 4 meters, which means that the measurement is non-contact. We then applied the methods proposed below to extract breathing rates. Butterworth filter is used to remove the unconscious body vibration from the chest motion (Figure 3). Then we extracted some parameters from ToF signals for machine learning, such as the mean and variance of the distance and the maximum point in the spectrum. In order to get an accurate breathing rate label, we used a temperature sensor to measure the temperature of the air in the nostril to represent the actual breathing rate. We compared different machine learning algorithms including Multivariate Linear, Stepwise Linear, Linear SVM and Cubic SVM, to estimate the breathing rate better.

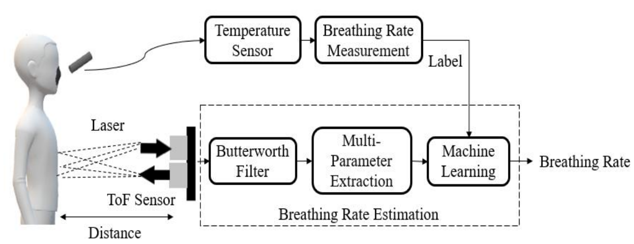

Figure. 1. System model

B. ToF Sensor

ToF stands for Time of Flight. The sensor sends continuous light pulses to the person, and then receives the light returned from him. By detecting the flight time of these emitted and received light pulses, the distance of the target object is obtained. TOF method is used to complete these related works [6] [7] [8].

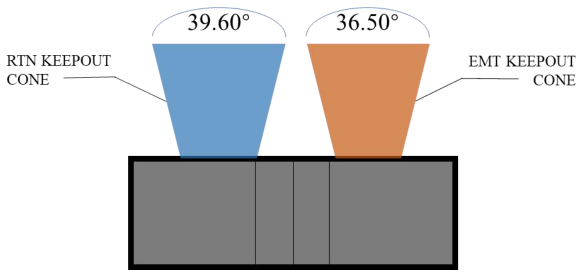

Figure. 2. Structure of ToF sensor

There are two methods to measure the distance with ToF. The method we use is based on continuous wave intensity modulation. An illuminated light is emitted and the distance is measured by using the phase change '$\Delta\varphi$' between the emitted and reflected light signals.

$$D = \frac{c}{2}\frac{\Delta\varphi}{2\pi f}$$

The general structure of a ToF sensor is shown in Figure 2. In this work we use a VL35L1X ToF sensor, which uses the second method. The 940nm laser is emitted from the EMT KEEPOUT CONE and received by the RTN KEEPOUT CONE. Through the official API, we can get millimeter scale measurements of distance from the 16×16 grayscale matrix obtained by the sensor. In addition, we can also correct the measurement data by the data validity, the number of returned photons and the number of photons interfered by ambient light, which are calculated from the matrix.

C. Multi-Parameter Extraction

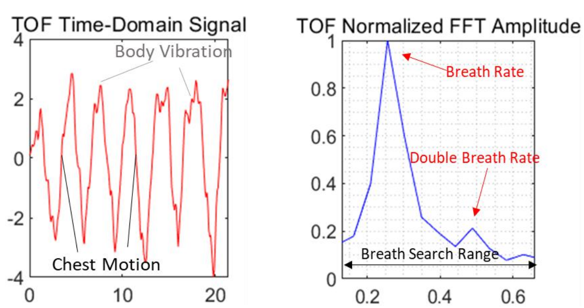

Figure. 3. Time domain and frequency domain of ToF signal

The mean, variance and peak frequency are the parameters we extracted. We first extracted the mean and variance of the distance in the time domain. As the breath signal is periodic, it can be clearly identified in signal phase (Figure 3). Then we extracted and estimated the breathing rate by performing Fourier transform of the phase of the signal (Figure 3). Since the normal breathing rate of human is between 0 and 40 bpm, we searched for the most significant peak of normal breathing within a predefined frequency range (e.g. 0.13-0.66Hz) [9]. The peak frequency is the rough estimate of breathing rate.

D. Machine Learning

The mean value, variance and peak frequency of the TOF signal are taken as input, the peak frequency of the temperature sensor signal is taken as label, and the output is the estimated breathing rate. Then we use four machine learning algorithms to estimate the breathing rate: Multivariate Linear, Stepwise Linear, Linear SVM and Cubic SVM.

Multivariate Linear regression uses the least square function of linear regression equation to model the relationship between multiple independent variables and dependent variable. This function is a linear combination of one or more model parameters called regression coefficients.

The hypothesis function is

$$h_\theta(x) = \theta^T x = \sum_{i=0}^{n} \theta_i x_i,$$

And the batch gradient descent update rule is

$$\theta_j := \theta_j - \alpha \frac{1}{m}\sum_{i=1}^{m} \left(h_\theta\left(x^{(i)}\right) - y^{(i)}\right)x_j^{(i)} \quad \text{(for all j)}$$

Once again, initialize the parameters to $\theta = \vec{0}$.

Stepwise Linear regression is to introduce variables into the model one by one and then test them. AIC is a commonly used criterion for Stepwise Linear regression. For regression equations containing p independent variables, n is the number of observed values (samples), and the smaller AIC is, the better. The specific calculation formula is

$$AIC = nh\frac{SSE}{n-p-1} + 2p + 2,$$

SSE is the sum of squares of residuals.

The Linear kernel is the simplest kernel function. It is given by the inner product <x, y> plus an optional constant c. Kernel algorithm using a linear kernel are often equivalent to their non-kernel counterparts, i.e. KPCA with linear kernel is the same as standard PCA [10].

$$k(x, y) = x^T y + c$$

The Polynomial kernel is a non-stationary kernel. Polynomial kernels are well suited for problems where all the training data is normalized. And the cubic kernel is expressed as follow

$$k(x, x_i) = (xx_i + 1)^3$$

III. Results

This section details the setup of the experiment, the overall performance of our algorithms and the analysis of the corresponding breathing rate estimation results.

A. Experiment Setup

As illustrated in Figure 4, we place the ToF sensor (VL53L1X) at the same height as the chest, facing towards the tester. At the same time, the tester holds the temperature sensor (MAX30102) to the nostril without covering the chest. And the sampling rate of the ToF sensor and the temperature sensor is 10Hz, which converts to the resolution of 100ms.

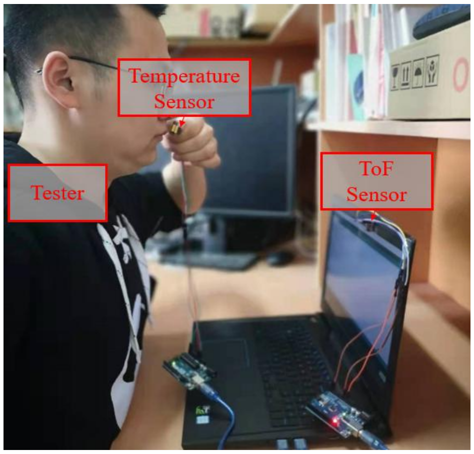

Figure. 4. Experiment setup

Experiments are carried out in groups, each group lasts 20 seconds. In order to validate the breathing rate estimation from ToF sensor, we recruit 6 participants to take part in this experiment. The experimental procedures involving human subjects described in this paper followed the principles outlined in the Helsinki Declaration of 1975, as revised in 2000. During the experiment, testers wear single coats, sit in front of the ToF sensor and breathe normally. In some experiment groups, we urge participants to speed up their breathing rate to ensure that the samples are more comprehensive. Both temperature signal and ToF signal are recorded and processed by the Arduino UNO board. Then we preprocess on the Arduino IDE through the API provided by the data manual to get the signal of distance change and temperature change, namely the preprocessed signal. Then we do Butterworth filtering and other subsequent processing on MATLAB.

B. Overall Performance

In this work, we use mean and variance in the time domain and frequency corresponding to spectrum peak of ToF signal as features, and take the actual breathing rate extracted from the temperature sensor as labels. Since we collected a total of 80 sets of data, we set the cross-validation folds to 8. Then we use these four algorithms for training, namely Multivariate Linear, Stepwise Linear, Linear SVM and Cubic SVM. The training results are shown in TABLE I.

TABLE I. BREATHING RATE ESTIMATION

	Algorithms			
	Multivariate Linear	***Stepwise Linear***	***Linear SVM***	***Cubic SVM***
ME	0.0105	0.0108	0.0094	0.0089
RMSE	0.0176	0.0181	0.0179	0.0166
R-Squared	0.92	0.91	0.91	0.93

ME = Mean absolute error (Hz), RMSE = Root mean squared error (Hz)

From TABLE I, we can conclude that R-squared values are all above 0.9, which means the models have good fitting effect. And RMSE values obtained by these algorithms are all below 0.02Hz, indicating that the measurement accuracy has reached the accuracy of most breathing rate detection instrument [11] [12]. Since the relationship between features and labels is not actually linear, the training effect of Cubic SVM is better.

Among them, the RMSE value obtained by Cubic SVM is the smallest, which is 0.0166Hz, and the mean absolute error is 0.0089Hz, corresponding to 0.534 breaths/min. These indicate that the method of obtaining breathing rate by ToF sensor is feasible.

We compared the results of the best performing Cubic SVM with several other methods for breathing rate detection in recent works, such as Airborne Ultrasound (AU) [4], Visible Light Sensing (VLS) [5] and Biophone (BP) [9]. The comparison results are shown in TABLE II. And The mean absolute error percentage was calculated based on the average breathing rate of 0.25Hz (15 bpm).

TABLE II. COMPARISON OF ESTIMATIONS BY DIFFERENT METHODS

	Methods				
	ToF	***AU***	***VLS***	***BP(Hand)***	***BP(Shoulder)***
MAPE	3.56%	5.33%	4.68%	1.89%	11.71%
RMSPE	6.64%	——	——	4.05%	22.6%

MAPE = Mean absolute percentage error, RMSPE = Root mean squared percentage error

From TABLE II, we can conclude that the mean absolute error percentage is 3.56% and the root mean squared percentage error is 6.64%, which is smaller than other methods of non-contact breathing rate detection including AU, VLS and BP(Shoulder). But compared with the method of contact detection, like BP(Hand), the accuracy of the system is still insufficient. As result, it shows that our method is effective for detecting breathing rate at a distance.

C. Use Issue Study

This section studies the impact of various issues for practical use of ToF, including the user-device distances, user different breathing rates and mean error distribution [13]. The following instructions are based on the model trained by the Cubic SVM algorithm.

User-device distance. We evaluated the performance of the model as the distance between the user and the ToF lens is various (Figure 5). The figure above shows the effect of distance. When the user is 0 - 80cm away from the ToF lens, the accuracy of the model is within the accuracy range of the current common breathing rate measuring instrument. Because the ToF lens uses 940nm laser and has a good filtering effect on the interference of non-strong ambient light, it makes up for the error caused by the longer moving distance to a certain extent. In fact, the precision measurement length of TOF can reach up to 4m, which has generally met the requirements of measuring distance.

Different breathing rates of the user. We measured a range of different breathing rates across different testers (Figure 6). Except for some "error points" with large frequency errors, the errors basically do not change with the vary of breathing rate, and are all within the required accuracy range. Except for some "error points" with large frequency errors, the errors basically do not change with the vary of breathing rate, and are all within the required accuracy range.

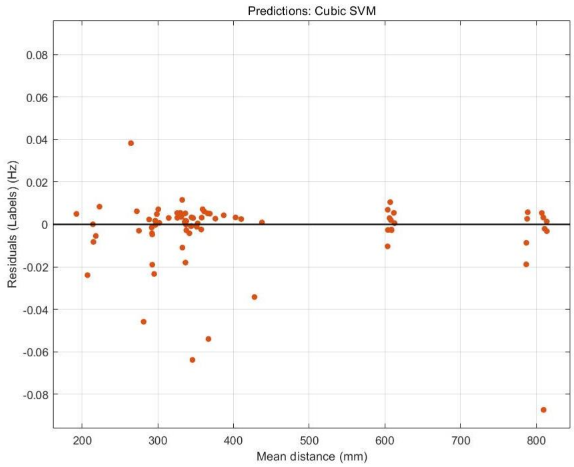

Figure. 5. Impact of user-device distance

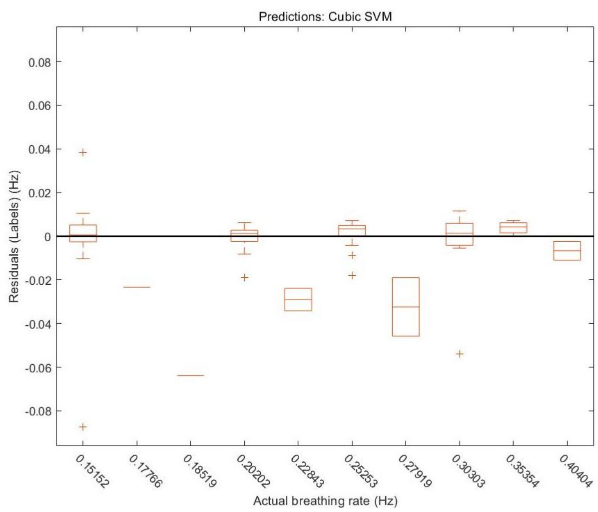

Figure. 6. Impact of different breathing rates of the user.

In the prediction of this model, most of the predicted values of breathing rate are within the required accuracy range (within 0.02Hz) (Figure 7). We believe that some of these residuals are large because the unconscious shaking of the tester's body is more intense than normal. This result indicates that it is difficult to get an accurate breathing rate through ToF if the body is shaking violently.

Influence of clothes. In the above experimental results we obtained, we ignored the effect of clothes on chest motion. But in practice, we need to consider this effect. From TABLE III, we can see that clothing has little influence on the TOF method, but clothes should not be so thick that it is hard to observe the chest motion.

TABLE III. INFLUENCE OF CLOTHES

	Wearing Clothes	*Without Clothes*
MAPE	4.60%	3.44%
RMSPE	8.04%	6.08%

MAPE = Mean absolute percentage error, RMSPE = Root mean squared percentage error

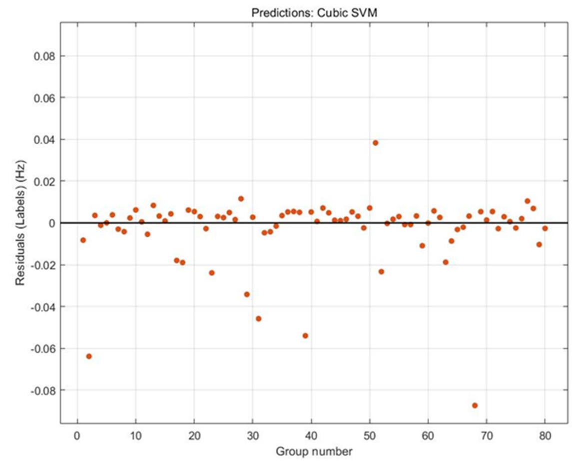

Figure. 7. Mean error distribution.

IV. CONCLUSION

In this paper, we propose a non-contact breathing rate detection method based on ToF sensor. First, we filter the distance change waveform collected by the ToF sensor. Then the characteristics are extracted. To achieve accurate breathing rate measurement, the phase, frequency and the actual breathing rate obtained by the temperature sensor are used in machine learning training. The results show that the ToF method has the same accuracy as the normal breathing rate measuring instrument, and the medium error of breathing rate is 0.017Hz. Now we have studied the measurement of breathing rate at rest, so further work focuses on monitoring breathing rate during user motion.

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