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A Real Time and Remote Intelligent Breathing Rate and Breathing Pattern Monitoring System

P. Suresh[1], A.Shivaram[2], P.Lavanya[3], V.Reshma[4], R.Pujith[5]
[1,2,3,4,5] *Department of ECE, Usha Rama College of Engineering And Technology, Telaprolu-521109, JNTUK, Kakinada, AP.*

Abstract— **The aim of this project is to develop an affordable real time remote intelligent breathing rate monitoring system. To achieve low-cost and remote measurement of respiratory signal, and Pi camera collaborated with marker tracking is used as data acquisition sensor, and a Raspberry Pi 4 is used as data processing platform. To overcome challenges in actual applications, the signal processing algorithms are designed for removing sudden body movements and filters are used for smoothing of raw signal. Subsequently, breathing rate is estimated by a translational cross point algorithm, and breathing pattern is identified by machine learning algorithms. For estimating respiratory rate, the translational cross point algorithm performs better than other methods with RMSE of 3.29 bpm. With respect to the classification of breathing patterns, the established machine learning performs better than other classifiers with the accuracy, precision, recall, and F1 score of 92.4%, 90.3%, 91.1%, and 90.5% respectively. The obtained decision-making information containing estimated breathing rate and pattern are sent to user's smartphone via a cloud service platform. In a way, due to its low-price, non-contact and portable merits, the system performs with high accuracy and robustness.**

Index Terms: **Breathing pattern, Breathing rate, Portable equipment, Physiological signal processing, Non-contact technique.**

I.INTRODUCTION

Breathing Rate (BR), commonly defined as the number of breaths per minute, is an important indicator of the health status and aids in identifying health abnormalities. The BR measure can serve as a predictor of critical illnesses. For instance, BR is screened in emergency departments of hospitals for indicating respiratory dysfunctions and predicting cardiac arrest. In primary care, BR can identify Apnea, Pneumonia and Pulmonary Embolism. Hence, monitoring BR can support effective triage decisions and facilitate the regionalization of critical care. Its continuous measurement is prominent for monitoring health conditions and it is typically measured as the number of Breaths per Minute (BPM). Breathing, however, has alternative functions aside from sustaining life. One researcher disclosed that the performance of respiration is regarded as a link between the states of the body and mind. More concretely, a person's state still as mood and stress could also be mirrored by illustration of breathing parameters. Once the person is healthy, breath comes naturally, effortlessly and while not thought, and this breathing condition is termed Eupnea viz. normal respiration. Abnormal respiration patterns, pertaining to abnormal respiration rate, depth and rhythm, ought to be of larger concern as a result of they can offer valuable reference for clinical designation, treatment and prognosis. The conventional techniques to measure respiration rate are contact-based and require sensors to be attached to the body, e.g. belt, or facemask. These sensors limit the movement of the patient. Moreover, in long-term monitoring, the sensor attachment to the body may lead to skin irritations and/or patient discomfort. For example, monitoring vital signs of burned skin patients or premature infants in the Neonatal Intensive Care Unit (NICU) requires the use of adhesives to attach sensors to their skin which might result in pain and skin irritation.

Lately, researchers[2], [8], [9], [10] have been focusing on the feasibility of measuring BR using camera through motion vectors related to the respiratory induced movements. Such remote measurement solutions can be applicable to situations where contact-based sensors are not desirable or feasible such as the monitoring of infants in neonatal intensive care, elderly individuals in senior care centres, patients in hospital emergency waiting rooms, and prisoners on suicide watch. The measurement is based on the principle that the inhalation and exhalation during breathing cause the chest and abdomen to rise and fall, which also brings slight movements of the ArUco marker pasted or printed on clothes. Therefore, a standard RGB camera can record these changes and track the movement of marker. Also, we note that previous video-based BR measurement studies present several shortcomings. Firstly, individuals were limited to slight movements. Specifically, for motion-based measurement techniques, it is challenging to differentiate between respiratory-induced motions and other movements that are unrelated to breathing. The proposed algorithm can estimate the BR if it receives a video containing ArUco marker placed on user's chest. For example, Tachypnea (rapid respiration) is one metabolism symptom of COVID-19 [1], therefore the prediction of Tachypnea could also be a relevant first order diagnostic feature which will contribute to large-scale screening of potential patients. For many application eventualities, it's necessary to watch the respiration condition for an extended time. Current thought methods used for clinical respiration observation embrace spirometer, capnometry and resistance pneumography. The advantage of those contact ways is being correct, but they may interfere with natural respiration and cause uncomfortableness. Several studies have enforced non-contact respiration measurements to cut back the uncomfortableness and inconvenience caused by contact ways. Consistent with the activity principle, the non-contact activity of respiration can be principally divided into 3 classes viz. measuring device Doppler effect primarily based methodology [12] , thermal imaging technology [8]and motion detection [11]. Whereas these ways have their individual deserves, they even have drawbacks. continued use of radars might create a possible risk of radiation unleash, and the measurement of breathing signal could also be disturbed by frequency bands close to the measuring device getting used. Thermal imaging cameras are at risk of close heat, and therefore the signal are lost if the tester's face isn't detected in difficult motion situations. The tactic supported motion detection could solve the higher than issues, however this technique needs the user not to move their bodies considerably.

II. LITERATURE SURVEY

Chen et al. [2] developed associate RGBthermal imaging system collaborated with marker sticker to achieve non-contact and correct respiratory rate measurement. Nonetheless, their system will solely describe the speed of the breath instead of amplitude or rhythm that successively fails to describe the user's respiratory condition well. Jiang et al. [4] planned a conveyable system with RGB-infrared sensors to notice metabolism infections. However, the thermal imaging camera is comparatively high-ticket. Yang et al. [6] proposed a C-band sensing technique primarily based breath observance system to identify diabetic ketoacidosis, however the system solely focuses on normal breath and Kussmaul breath. Wang et al. [3] proposed a period of time system with depth camera for classifying multiple people's metabolism patterns. The system will be applied to the multi-people scenario in an exceedingly period of time manner. The most important obstacles to the commercialisation of the system are the high cost and issue of algorithm migration. There still stay several open inquiries to remotely monitor users' respiratory condition in home and work eventualities. Inspired by the previous researches, a noncontact breathing rate monitoring system appropriate for health care must meet the subsequent needs: (1) accuracy and strength are the foremost important; (2) it ought to be a time period and online system which may show the user's respiratory conditions in a timely manner (3) the system is to be simple to install and register [4] and (4) the complete system ought to be low-cost.

Therefore, we tend to develop an inexpensive and remote intelligent breathing rate and breathing pattern monitoring system. In this system, the variance-based algorithmic program is developed to remove vital body movements and preserve respiratory related signals; the change of location cross purpose algorithmic program is developed to estimate breathing rate; and also the machine learning model is established to classify breathing pattern. The custom dataset is established to validate system strength once user's move at a low frequency.

III. METHODOLOGY

The main work flow of this technique is as follows. ThePi camera initial tracks the marker sticker on user's chestto obtain the raw signal. The Raspberry Pi laterexecutes the signal process algorithms each one minute.The translational cross point algorithm and therefore the machine learning algorithms severally developed for respiratory rate estimationand respiratory pattern classification victimization the processed signal.These algorithms and models are valid on ourCustom dataset, and that they outstrip alternative ways on our task (section III). Finally, the information as well as time, breathing rate and breathing pattern is transmitted to user's smartphone via wireless transmission. The user will see the respiratory condition in a very period manner, check the statistical analysis of respiratory pattern and respiratory rate in last twenty minutes, and query the history of respiratory condition.

A. Overview of the real time and remote intelligent breathe rate monitoring system

The breathing condition system prototype is shown in Fig. 1. It contains one Raspberry Pi 4B, one Pi camera and power supply. The Raspberry Pi 4B is employed for execution algorithms and sending results to smartphones; the RGB Pi camera is employed for getting raw respiratory signal by tracking the marker on user's chest;and batteries build the whole device freelance of external power; the algorithms on the Raspberry Pi change the system to live respiration rate and acknowledge respiration patterns.

This system is compact, light-weight and cheap, creating it appropriate for varied actual application Scenarios. Due to the characteristics mentioned on top of, we call this breathing condition assessment system "Breathing Rate Monitor". Data stream of this technique is shown in Fig. 2. In this system, the Raspberry Pi is employed for getting the raw signal, processing the signal, estimating respiratory rate and classifying breathing pattern, which will be elaborated in coming sections. The respiratory information is transmitted via a ThinkView cloud service platform and shown in the user interface. This technique is implemented by OpenCV with Python. For the present version, this system are often simply migrated to alternative compact devices.

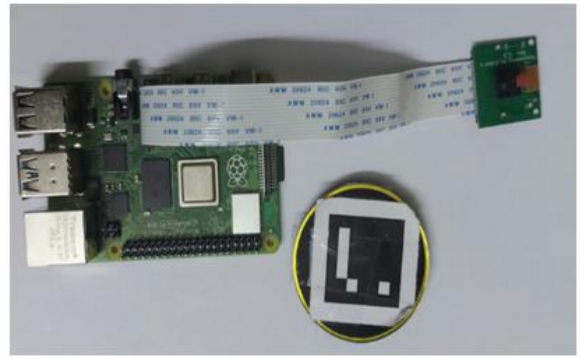

Fig. 1: Prototype of Breathing Condition Monitoring System.

B. Acquisition of Raw Signal

As shown in Fig. 2, a Pi camera with resolution of 720P is used to record the placement of the ArUco marker in every frame to get the raw breathing signal. ArUco is a library for increased reality applications primarily based on OpenCV the inhalation and exhalation throughout respiration cause the chest and abdomen to rise and fall that conjointly brings slight movements of the ArUco marker glued or printed on clothes.

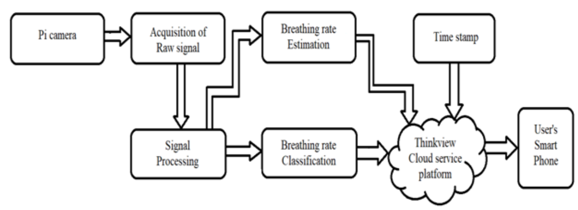

Fig. 2: Data stream of the respiratory monitoring system. The Pi Camera frame is transmitted to Raspberry Pi; the breathing signal flows inside the Raspberry Pi; and the breathing condition data is transmitted to smartphones via a cloud service platform.

We've got tried to extract X and Y positions (corresponding to the horizontal and vertical components) of the marker in every frame, and also the Y position is found to be more appropriate for describing respiration. Previous researches conjointly incontestable that the horizontal part (X position) contains most of body-balancing movements unrelated to respiration rate, thus it's reasonable to discard it once the subject is facing the camera.

C. Signal processing method

The raw signal contains noise caused by non-contact measure and is vulnerable to the unforeseen movements of the human body. In actual usage, the user might move the body in a short time, like getting up from a chair. Therefore, the signal process is important for the following calculation and analysis. For the unforeseen movements, we tend to adopt a time domain threshold to tell apart the distinction between slight breathing movements and vital body movements. For the noise caused by non-contact measure, we tend to adopt Band Pass Filters to smooth the signal.

1) Removal of significant body movements: The body movements are much more intense than breathing movements, so we tend to adopt a threshold for the variance to work out whether or not a part of signal is caused by body movements or respiration. For each signal yk, we tend to place short windows with length of Lsw and calculate the variance of every window. If the variance is larger than the pre-set threshold, this window is assumed to be vital body movements and is removed. Finally, the remaining windows are normalized severally by the following equation and spliced into the ultimate signal.

$$\hat{y}_{sw}(k) = \frac{y_{sw}(k) - \min[y_{sw}(k)]}{\max[y_{sw}(k)] - \min[y_{sw}(k)]} \tag{1}$$

This method is demonstrated in Algorithm. The value of threshold is vital to tell apart respiration connected signals and body movement signals. In most cases the variance of the breathing signal in a very short term is below 10 pixels, whereas the variance of the body movement signal is higher than 30 pixels.

2) Signal smoothing: when removing body movements, we adopt Kalman Filter to swish the signal. During this study, the respiration signal is delineated by a dynamic model.

$$\boldsymbol{X_k} = \begin{bmatrix} p_k \\ v_k \\ a_k \end{bmatrix} = \begin{bmatrix} 1 & dt & 0 \\ 0 & 1 & dt \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} p_{k-1} \\ v_{k-1} \\ a_{k-1} \end{bmatrix} \tag{2}$$

WhereXk represents the system state at time k; pk is that the position of the ArUco marker; vk is that the

$$\boldsymbol{X_k = F_k X_{k-1} + B_k \mu_k} \tag{3}$$

$$\boldsymbol{P_k = F_k P_{k-1} F_k^T + Q_t} \tag{4}$$

speed of chest movements; and ak is the acceleration of chest movements.In the prediction stage, Xkand its covariance Pk can be predicted from Xk-1 and Pk-1:

$$\boldsymbol{K_k} = \frac{\boldsymbol{P_k H_k^T}}{\boldsymbol{H_k P_k H_k^T + R_k}} \tag{5}$$

$$\boldsymbol{X_{opt}} = \boldsymbol{X_k} + \boldsymbol{K_k}(z_k - \boldsymbol{H_k X_k}) \tag{6}$$

$$\boldsymbol{P_{opt}} = (\boldsymbol{I} - \boldsymbol{K_k H_k})\boldsymbol{P_k} \tag{7}$$

Where Fk is the state-transition model in equation (2); Qtis the covariance of the process noise; and Bk_krepresents the control input which is not taken into consideration in this study, so it can be omitted. In the update stage, Xk and Pkcan be updated by Gain Kk: Where Hk is that the observation model; zk is associate degree observation viz. the Y-position of the marker; and Rk is the covariance of the observation noise. The signal are smoothened by repeating equation 3 to 7 with Xopt and Popt. The aim of this operation is to facilitate the calculation of breathing rate and the classification of breathing pattern. Fig.3 showsone example of raw signal and filtered signal output. The burst signal caused by body movement is removed, and therefore the processed signal gets smoother.

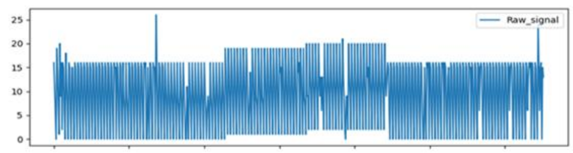

Fig. 3: One example of the signal processing method: (a) the raw signal (b) the filtered output.

D. Breathing rate estimation

The respiratory rate can be estimated from the processed signal via a translational cross point algorithm. First, we move the signal yk to the right by w points and write it as yk,w. Second, we calculate the number of cross points between ykand yk,w, and write it as cw. The final respiratory rate is calculated based on the length of the data and cw. This method can be represented by equation

$$\boldsymbol{RR(bpm)} = \frac{c_w/2}{\boldsymbol{N/F_s}} * 60 \tag{8}$$

Where RR(bpm) represents respiratory rate (beats per minute); cw is the number of cross points between ykand yk,w; N is the length of the data; and Fsis sampling rate. One example of estimating respiratory rate from a normal breathing waveform is shown in Fig. 4.

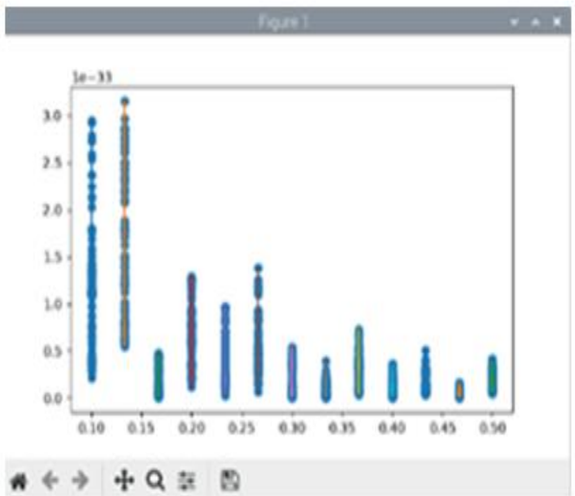

Fig. 4: Estimation of Breathing Rate.

E. Breathing pattern classification

There square measure 2 drawbacks of the projected breathing rate estimation method: (1) once abnormal respiratory like a short amount of physiological condition happens, the performance of the proposed vital sign estimation methodology are going to be greatly influenced; and (2) vital sign solely reflects the speed of respiratory, and it cannot concretely and comprehensively describe the breathing state. For these 2 reasons, it is necessary to classify user's breathing pattern through the processed waveform.

As a long-standing analysis topic in machine learning, diverse classification models are projected. The classification model employed in this study relies on machine learning algorithms. The neural network during this model is named BI-AT-GRU, which is a variant of the Gated Recurrent Units (GRU) network with two-way and basic cognitive process mechanisms. BI-GRU layer captures bidirectional info within the respiration signal, which can be depicted as:

$$\overrightarrow{h_t} = \overrightarrow{GRU}(x_t), \qquad t \in [1, n] \tag{9}$$

$$\overleftarrow{h_t} = \overleftarrow{GRU}(x_t), \qquad t \in [n, 1] \tag{10}$$

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \tag{11}$$

Where xt is respiratory signal at time t; n represents the period of a respiratory pattern; and GRU (.) represents gated recurrent unit.The attention layer focuses on important points in the respiratory signal, which can be represented as:

$$u_t = \tanh(W_a h_t + b_a) \tag{12}$$

$$\alpha_t = softmax(V_a u_t) \tag{13}$$

$$S = \sum_t \alpha_t h_t \tag{14}$$

Whereht is that the state of t step, that is that the same in equation (11); Wa, ba and Va are the parameters obtained by training phase; the add of αtht at every purpose is calculated and is denoted as S. Eupnea, Bradypnea, Tachypnea and Apnea represent traditional breath, slow breath, fast breath and asphyxia, respectively. These four patterns are the foremost common, and that they mix with one another to create another advanced respiratory patterns

F. Detection Reports

The breathing condition data is sent to user's smartphone via the wireless transmission. The particular method is as follows. When the Raspberry Pi gets breathing rate and breathing pattern, it transmits the data to the cloud service platform in the format of 'DD-MM-YYYY hh:mm:ss' with associate communications protocol POST request. In this string, 'DD-MM-YYYY hh:mm:ss'Represents time, breathing pattern and breathing rate are displayed consequently. The cloud service platform stores the respiratory data in chronological order. In this study, we chooseThink View as the cloud service platform, and it may be replaced according to as the usage. Once the user enters the interface and clicks the refresh button, the breathing data is transmitted from the cloud to the smartphone via associate communications protocol GET request. As shown in Fig. 5, the user interface contains the real time breathing condition.

IV.EXPERIMENTS AND RESULTS

A. Dataset Establishment

The aim of the experiment is to validate the robustness of the system for breathing rate estimation and breathing pattern classification at simulated daily work situation. Subjects sat in a relaxed manner and imitated breathing patterns (Eupnea, Tachypnea, Bradypnea, and Apnea) for one minute, with a one-minute break between every pattern.

Fig. 5: The user interface in the smartphone contains the real-time breathing condition.

Throughout activity, they may move their bodies to simulate sensible eventualities, like adjusting the position, using the smartphone and working on the laptop. The established monitor was placed at 2m from the user. The marker was affixed to subjects' chest. Videos from Pi camera were recorded to ascertain the respiratory pattern and analyze inaccurate activity. A total of ten folks participated within the experiment. There are 600 samples within the dataset. The marker sticker is attached up to the user.

B. Breathing Rate

For breathing rate (BR), we compare the translational cross point algorithm with Fast Fourier Transform (FFT) method and curve fitting method. FFT method takes the frequency with maximal power in the pass band of [0:1; 0:8] Hz as the respiratory rate. We choose root mean square error (RMSE), mean absolute error (MAE) and calculation speed as the performance evaluation indicators. Results listed in Tab.I demonstrate that the translational cross point algorithm has the lowest RMSE. Besides, the translational cross point algorithm is faster than and performs better than FFT method. Thus, we finally choose translational cross point algorithm in our system. The performance of BR estimation specific to four breathing patterns is demonstrated below. This suggests that the BR estimation method does not add some abnormal breathing patterns such as apnea, and this is this is reason to add the respiratory pattern classification model into the system.

TABLE I: Performance Comparison of Different Methods for Estimating Breathing Rate

BR Estimation Method	RSME(bpm)	MAE(bpm)
Translational Cross Point	3.29	2.33
FFT	5.33	3.69

C. Breathing Pattern

For breathing pattern, we compare machine learning with BI-AT-GRU model with the models based on support vector machine (SVM). Features designed for SVM are same. Training BI-AT-GRU needs abundant synthetic data generated by respiratory simulation model (RSM), while training SVM is not necessarily required abundant data.

S. No.	Performance Parameters	Existing Methods		Proposed Method
		SVM & RSM	SVM & TENFOLD	BI-AT-GRU & RSM
1.	Accuracy	66.0%	72.7%	92.4%
2.	Precision	66.0%	73.1%	90.3%
3.	Recall	66.0%	71.0%	91.1%
4.	F1 Score	65.4%	69.0%	90.5%

TABLE II: Performance Comparison of three Breathing Pattern Classification Models.

The results listed in Tab.II demonstrate that BI-ATGRU performs better than models based on SVM. The machine learning model in research can recognize the respiratory pattern with accuracy, precision, recall, and F1 of 92.4%, 90.3%, 91.1%, and 90.5%, respectively. In this study, subjects could move their bodies significantly. This study focuses more on complex usage scenarios and low costs under the premise of relatively high reliability. Performance evaluation of breathing pattern classification specific to four breathing patterns is shown.

V. CONCLUSION

In this pro, we propose a non-contact, low-cost and compact system for breathing condition assessment. By leveraging the proposed signal processing algorithm and the recurrent neural network pre-trained by Respiratory Simulation machine learning Model, the developed breathing condition monitoring system can simultaneously derive the breathing rate and the breathing pattern under various scenarios. A custom dataset is established to validate system robustness. For estimating respiratory rate, the translational cross point algorithm performs better than other methods with RMSE of 3.29 bpm. With respect to the classification of breathing patterns, the established machine learning classifiers performs better than SVM-based classifiers with the accuracy, precision, recall, and F1 of 92.4%, 90.3%, 91.1%, and 90.5%, respectively.

Compared to previous work, our system is relatively closer to practical applications and has potentials to land because of low-cost and compact characteristics along with algorithms specific to complicated actual scenarios. Therefore, this system can be seen as a “breathe monitor”. Experiments in 10 subjects validate the system robustness when there are only low frequency body movements, such as playing smartphones and reading books.

REFERENCE

[1] M. Cascella, M. Rajnik, A. Cuomo, S. C. Dulebohn, and R. Di Napoli, “Features, evaluation and treatment coronavirus (covid-19),” in Statpearls [internet]. StatPearls Publishing, 2020.

[2] L. Chen, M. Hu, N. Liu, G. Zhai, and S. X. Yang, “Collaborative use of rgb and thermal imaging for remote breathing rate measurement under realistic conditions,” Infrared Physics & Technology, vol. 111, p. 103504, 2020.

[3] Y. Wang, M. Hu, Y. Zhou, Q. Li, N. Yao, G. Zhai, X.-P. Zhang, and X. Yang, “Unobtrusive and automatic classification of multiple people’s abnormal respiratory patterns in real time using deep neural network and depth camera,” IEEE Internet of Things Journal, 2020.

[4] Z. Jiang, M. Hu, Z. Gao, L. Fan, R. Dai, Y. Pan, W. Tang, G. Zhai, and Y. Lu, “Detection of respiratory infections using rgb-infrared sensors on portable device,” IEEE Sensors Journal, 2020.

[5] X. Yang, D. Fan, A. Ren, N. Zhao, and M. Alam, “5g-based user-centric sensing at c-band,” IEEE Transactions on Industrial Informatics, vol. 15, no. 5, pp. 3040–3047, 2019.

[6] M. Hu, G. Zhai, D. Li, H. Li, M. Liu, W. Tang, and Y. Chen, “Influence of image resolution on the performance of remote breathing rate measurement using thermal imaging technique,” Infrared Physics & Technology, vol. 93, pp. 63–69, 2018.

[7] M. Hu, G. Zhai, D. Li, Y. Fan, H. Duan, W. Zhu, and X. Yang, “Combination of near-infrared and thermal imaging techniques for the remote and simultaneous measurements of breathing and heart rates under sleep situation,” PloS one, vol. 13, no. 1, p. e0190466, 2018..

[8] H. Zhao, H. Hong, D. Miao, Y. Li, H. Zhang, Y. Zhang, C. Li, and X. Zhu, “A noncontact breathing disorder recognition system using 2.4-ghz digital-if Doppler radar,” IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 1, pp. 208–217, 2018.

[9] A. Proch´azka, H. Charv´atov´a, O. Vyˇsata, J. Kopal, and J. Chambers, “Breathing analysis using thermal and depth imaging camera video records,” Sensors, vol. 17, no. 6, p. 1408, 2017.

[10] O. Gupta, D. McDuff, and R. Raskar, “Real-time physiological measurement and visualization using a synchronized multi-camera system,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2016, pp. 46–53.

[11] S. Wiesner and Z. Yaniv, “Monitoring patient respiration using a single optical camera,” in 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE, 2007, pp.2740–2743.

[12] S. Ivashov, V. Razevig, A. Sheyko, and I. Vasilyev, “Detection of human breathing and heartbeat by remote radar,” in Progress in Electromagnetic Research Symposium, vol. 2004, 2004.