Remote Detection and Classification of Human Stress Using a Depth Sensing Technique

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T. Chen
Southwest University in Chongqing

Wu Zhan
Southwest University in Chongqing

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Yuhao Shan
Chongqing Key Laboratory of Nonlinear Circuit and Intelligent Information Processing Southwest Universit y
Chongqing, 400715, China

Tong Chen*
Chongqing Key Laboratory of Nonlinear Circuit and Intelligent Information Processing Southwest University
Chongqing, 400715, China
*Email: c_tong@swu.edu.cn

Liansheng Yao
Chongqing Key Laboratory of Nonlinear Circuit and Intelligent Information Processing Southwest University
Chongqing, 400715, China

Zhan Wu
Chongqing Key Laboratory of Nonlinear Circuit and Intelligent Information Processing Southwest University
Chongqing, 400715, China

Wanhui Wen
Chongqing Key Laboratory of Nonlinear Circuit and Intelligent Information Processing Southwest University
Chongqing, 400715, China

Guangyuan Liu
Chongqing Key Laboratory of Nonlinear Circuit and Intelligent Information Processing Southwest University
Chongqing, 400715, China

***Abstract*—Stress plays an important role in our daily life. Long-term's psychological stress will lead to serious health as well as social problems, it is important to detect and monitor the psychological stress in its early stage. Most existing stress detection equipment are contact-type, such as wrist strap. However, in a real application, such as a working environment, a contact-free stress detection system will bring greater convenience. In this paper, we proposed a novel framework for detecting and classifying human stress based on respiratory signals measured remotely by using a Kinect sensor with a detection range of 3 meters. We test the framework on respiratory signals data set from 20 individuals under 3 different tasks (listen relax music, do exercise and do Stroop Color-word test), corresponding to relaxation, physical stress and psychological stress state. Experimental results suggest that the proposed method is a promising way for monitoring human stress and even discriminating psychological stress from the physical stress.**

***Index Terms*—stress detection, stress classification, remote sensing respiration signal, physiological features of stress**

I. Introduction

Human stress is an imbalance state of an individual. Stimulus threatening homeostasis state of the individual is regarded as a stressor, which can be classified into physical one or psychologic one. A physical stressor has a direct effect on the individual's body. It may be an external uncomfortable condition (heat, cold, etc.), or due to internal demands of the body. A psychological stressor has no direct physical impact on the body. It is perceived by the individual as a threat [1].

Because of unhealthy effects of stress and wide application of stress detection, the research of stress detection has attracted interest of both engineers and psychologists. Traditional physiological-based detection methods [2] [3] require sensors to be attached to individuals during stress detection, which are awkward for operation. To overcome this inconvenience, imaging techniques, such as thermal imaging (TI) [4], hyperspectral imaging (HSI) [5] [6], and broadband imaging [7], have been used for the detection. Pavlidis et al. [8] [9] used TI to measure the blood flow under skin surface and the perspiration of nose for the detection. McDuff et al. [7] used five band digital camera to measure heart rate variability (HRV) for the detection. We used HSI to measure tissue oxygen saturation for the detection [5].These imaging techniques share a common characteristic of being able to detect stress remotely based on physiological signals, which provides more comfort to testees.

However, all these studies focus on the detection of psychological stress. Physical stress shares similar features with those of psychological stress, such as raised heart rate [5], respiration rate, muscle tension [10], perspiration [9], etc. It could be detected as psychological one if the context is unknown or physiological features are not selected properly. For example, in the application of detecting a computer user's psychological (mental) stress in a working environment, the user could return to work in a physical stress state after a brisk walk. The physical stress that the user has could be a 'noise signal' for the psychological detection. It is thus of interest to investigate how physical stress can be discriminated from psychological one by using imaging techniques.

In one of our pilot studies [1], we investigated the possibility for discriminating psychological stress from physical one using the TI technique, and presented facial temperature maps of two candidates under different stress state. We would like to investigate possible techniques further, which can be used in an office or home environment for remote detecting psychological stress without taking physical stress as a false alarm.

In this paper, we propose a framework for remotely detecting human stress and discriminating two types of stress of 20 volunteers using a depth sensing technique.

Specifically, we used a Kinect to obtain depth signals of thoracic cages and abdominal cavities of the users in sitting positions, developed an algorithm for extracting respiration signals from the depth signals, generated 30 features from respiration signals, and classified relaxation, physical, and psychological stress states by using three fisher classifiers.

II. REMOTE MEASUREMENT OF RESPIRATION SIGNALS

A. Microsoft Kinect and Depth Sensing

The Microsoft Kinect is a low-cost imaging system. It was originally designed for motion detection in game control. A Kinect consists of a RGB camera and a depth sensing system. The RGB camera works as a normal broad band image system with a complementary metal-oxide-semiconductor (CMOS) sensor. The depth sensing system has an infrared emitter and a CMOS sensor. Structured speckles are emitted from the emitter and reflected by objects in the field of view of the Kinect. The distance between the objects and the Kinect modulates the patterns of the reflected speckles that captured by the CMOS sensor. By comparing the reflected pattern and a referenced pattern, the distance (depth) can be determined. There are three resolution settings for a depth image, i.e. 640*480,320*240, and 80*60. In this paper, the resolution of 640*480 was chosen for giving more details. The frame rate for the depth video is 30fps. Every pixel within a depth image is allocated a vector value (X, Y, D). The X and Y represent the coordinate values, and D represents the distance between the pixel and the Kinect.

The Kinect can recognize one to six users in the field of view. Skeletal Tracking in Kinect can locate the joints of up to two users and record the motion of the joints over time.

B. Obtaining respiration signals

Respiration modulates fluctuation of the thoracic and abdominal parts when the body is still. The Kinect can sense the fluctuation and deduce the respiration signals. The thoracic and abdominal parts are obtained by using Skeletal Tracking function in Kinect. As shown in Fig 2, Kinect can locate 20 joint points of human body in whole body mode, or locate 10 joint points in seated mode (point in red, Fig2 (c)). We choose seated mode in this paper, for it is more adaptable and more robustness in everyday application environment that only need the upper body appears in the view of the camera. Four joint points used for determining the thoracic and abdominal parts are head point (point 2, Fig1 (a)), left shoulder point (point 10, Fig1 (a)), right shoulder point (point 9, Fig1 (a)), and shoulder center point (point 2, Fig 1 (a)). Firstly, we get the distance between head point and shoulder center point h, and get the distance between left shoulder point and the right shoulder point w, then, the thoracic part and abdominal part are determined by w and h, respectively, as shown in Fig 1 (c)).

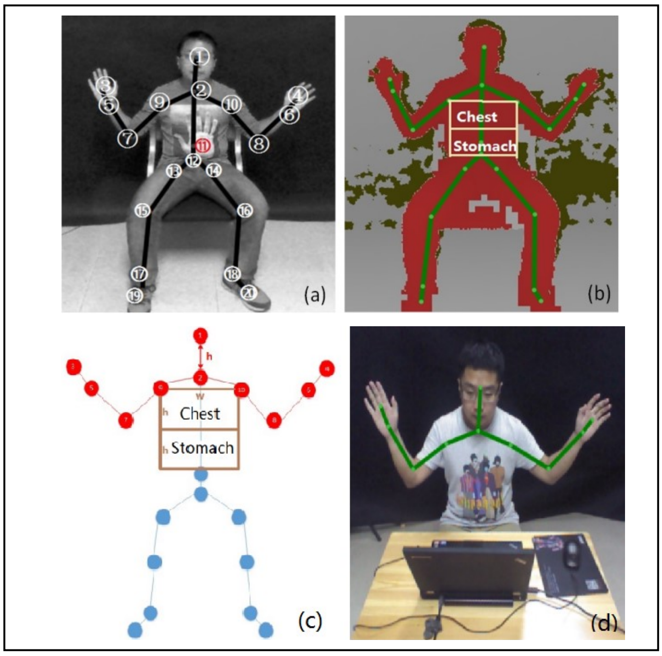

Fig. 1. (a) Joints located by Kinect under whole body mode; (b) thoracic part and abdominal part determined by joint points for respiration signal measurement; (c) Definition of thoracic part and abdominal part; (d) Joints located by Kinect under seated mode;

Depth values within the thoracic and abdominal parts are averaged to remove the noise due to creases of clothes. The average depth value of thoracic or abdominal is a function of time, which is regarded as respiration signal.

To improve their solution of depth sensing, the angle between axis of Kinect sensor and plane of chest wall is required to smaller than 90° . Xia at al [29] made this angle as small as 5° when a testee was in a supine position. In this research, we found that an angle of no more than 67° was enough for obtaining respiration signal when a testee was in a sitting position. The angle was thus set as 67° (see Fig 2).

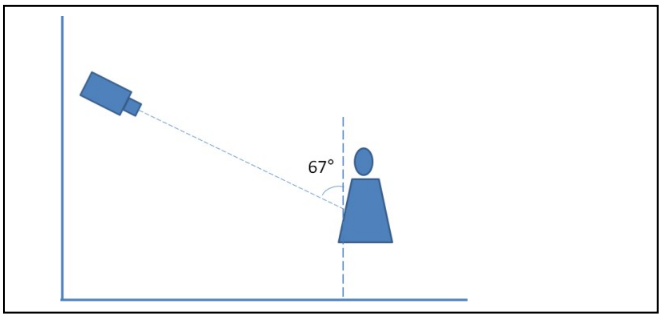

Fig. 2. Illustration of viewing angle setup between a Kinect and a testee.

We have developed a software system using C# for displaying the respiration signal as function of time in real time. Fig 3 shows the GUI of the system and a segment of respiration signal obtained from Kinect under different

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breathing patterns, which are normal breath, deep breath, and holding breath. It is observed that different breathing patterns are distinctive to each other in terms of signal curve. A contact respiration monitor (Biopac MP150) is used together with the Kinect for recording respiration signal of ten testees. The comparison of respiratory signals collected by MP150 and Kinect are shown in Fig 4. As we can see, their trends are very consistent. The correlation coefficient of Kinect signal (sitting still) and MP150 signal is 0.99. A txt file is generated for recording the respiration signal alone side the GUI running. It will be saved on the hard drive of the PC connecting the Kinect for later analysis.

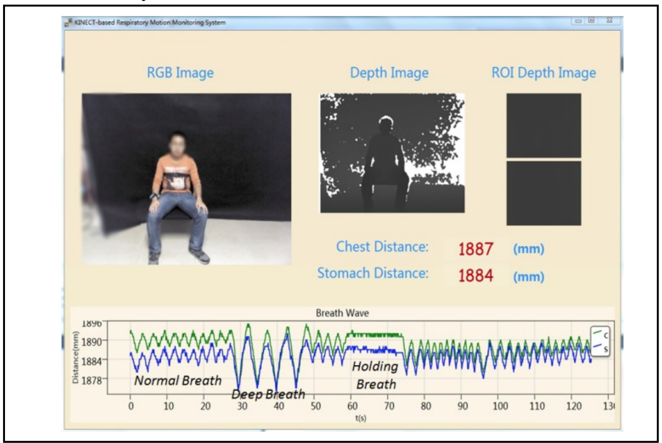

Fig. 3. A GUI of the software system for controlling Kinect and recoding respiration signal. A segment of respiration signal is shown in the bottom of the GUI. The blue trace is the mean depth of stomach, the blue is chest.

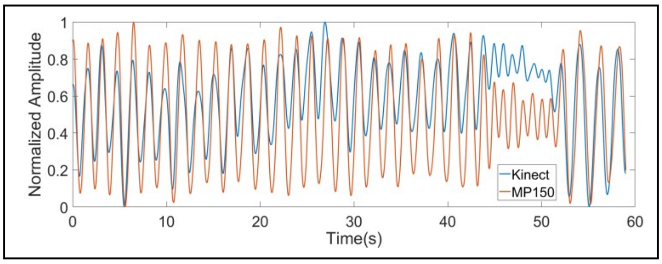

Fig. 4. Comparison of RSP signals collected by Kinect and MP150

C. *Experimental Procedures and Protocols*

20 volunteers were recruited to participate in the human stress test. They are undergraduate students at the age of 18 to 23 within Southwest University. Half of the participants are male, the other half are female. All participants are healthy without color blindness or diseases of respiratory or cardiac systems. The experiments procedures were proved by local Ethics Committee of Southwest University. A written consent of every participant was obtained before any experiment. All the experiments were conducted in an indoor environment. The room temperature was 26 degree centigrade. Two ordinary fluorescent lamps were used as illumination source. The setup of the experiment is shown in Fig 5.

The participant was welcomed and spent 10 minutes to adapt to the experimental environment. During the 10 minute, the participant was introduced the procedure details of the experiment. After the 10 minute, the experiment was about to start if the participant agreed to the informed consent. The whole experiment consisted of four tests in sequence, i.e. baseline test, relaxation test, psychological stress test, and physical stress test. During the signal acquisition, the participant sat calmly as shown in Fig 5. The distance between the participant and the Kinect sensor was about 2 meters. The participant leaned on the back of chair comfortably but was not required to sit still, occasional body movement was allowed just like real working environment. But only the video sequence in which the participants was sitting still will be used for further analysis to avoid the effect of body movement to the depth sensing of thoracic and abdominal parts. Between each test, the participant had 5 minutes to rest and make his/her state back to baseline.

Fig. 5. Experiment setup

During the baseline test, the participant was required to be seated calmly and comfortably for 5 minutes.

During the relaxation test, the participant sat calmly and listened to the relaxing music for 5 minutes.

The psychological stress test was performed by using the Stroop Color-Word Test. There are 100 stimuli for the test. Each stimuli was presented in a slide. On each slide, one of four words (Red, Blue, Green, and Yellow) was shown in a color other than the meaning of the word, e.g. word 'Red' was shown in blue. The participant was required to choose the meaning of the word or color of the word randomly. Before the test, the participant was told if he can make more right choose than average, he/she can get CNY20 as a reward. The answering time for each slide was 5 seconds in the beginning of the test, and it gradually decreased to 3.5 seconds in the end of the test to increase the difficulty.

The physical stress test is to ask the participant to make 20 to 40 body weight squats. The participant can stop if he felt that more than moderate physical demand was needed for doing the squat.

The respiration signal was continuously measured during the baseline, relaxation, and psychological stress test. For the physical stress test, the signal was measured when the participant finished the squat and sat back comfortably on the chair. The measurement lasted for 5 minutes.

After the tests, the participant was required to evaluate psychological and physical stress level during the tests using 1-10 scales. Only the signal with level 6 or more will be used as candidate signal for the stress detection analysis. All the participants reported that their stress level (both psychological and physical) are more than 6. Therefore, there are 30 segments of respiration signals in every test. For four tests, there are 120 segments of respiration signals available for the stress analysis. Each segment of respiration signal lasts for about 5 minutes (300 seconds).

III. DETECTING AND CLASSIFYING HUMAN STRESS

A. *Preprocessing of the respiration signal*

To remove noise, such as baseline drift and system noise, a band-pass filter was employed. For the baseline and relaxation test, the pass band was set as 0.1-0.6Hz, considering that respiration frequency under calm state is about 0.1-0.35Hz. For the stress test the pass band was set as 0.1-1Hz, considering that respiration rate increases under stress state but may not reach 60times per minute (1Hz).

Each segment of the respiration signals was smoothed every 0.5 second after it passed the band-pass filter. After the smoothing, the short-term fluctuations were removed. The local maxima and minima of the respiration signal will purely represent the exhaling and inhaling peaks of the body, respectively.

To make every signal segment (300s long in time) correspond to the effective arousal and be the same length, a 60s sub-segment was selected from every segment. For the baseline and relaxation test, the sub-segment was selected from 101s-200s of every segment, considering that the participant had adapted to the environment and may not be affected by the following stress test during this period. For the psychological stress, the sub-segment was selected from 201s-300s, considering that psychological stress should have effect on the participant during this period. For the physical stress test, the sub-segment was selected from the 21s-120s, considering that subjects' breathing has been relatively smooth, and the effect of physical stress was strong during this period.

B. *Feature extraction and selection*

A total of 20 typical time domain features were obtained from respiratory signals, they are the mean(1), variance(2), standard deviation(3), median(4), interquartile range(5), kurtosis(6), skewness(7), root mean square(8), minimum(9) and maximum values(10) as well as the mean of the first and(11) the second derivative(12), respiration cycle time(13), respiration rate(14), inspiratory flow(15), inspiration time(16), respiration amplitude(17), inspiratory duty cycle time(18), and mean of post-expiratory pause series under two different threshold(19, 20).

10 domain features were also been considered. They are summing and mean energy in the bands 0.1-0.2Hz(21, 22), 0.2-0.3Hz(23, 24), 0.3-0.4Hz(25, 26), 0.4-0.5Hz(27, 28) and 0.5-0.6Hz(29, 30).

All the features extracted under the baseline test were subtracted from the features extracted under the stress tests and relaxation test to avoid the effect of individual difference. Then, student's t-test were employed to select the useful features. A feature under three test, i.e., relaxation test, psychological stress test, and physical stress test, can produce three vectors. The feature will be regarded as useful if the t-test between any two vectors gives significant difference ($p<0.05$).

After the t-test, there are 14 features selected out that can be used to discriminate relaxation from other affective states (Features number: 2, 3, 5, 8-10, 13-17, 20, 27 and 28), there are 12 features selected out that can be used to discriminate psychological stress from other affective states (Features number: 2, 3, 5, 8-10, 15-16, 23-24 and 27-28), there are 15 features selected out that can be used to discriminate physical stress from other affective states(Features number: 2, 3, 5, 8-10, 15-16, 19 and 25-30). Since there is information redundancy among the selected features, the PCA algorithm was used for dimensionality reduction of these feature matrices. After testing, it is found that the first four principle components can achieve the best performance if they are used to detect relaxation state and physical stress state, the first seven principle components can achieve the best performance if they are used to detect psychological stress state.

C. *Detection and classification*

After feature selection and dimensionality reduction, three one-to-many fisher classifiers were used to classify the three states, i.e., relaxation, psychological stress, and physical stress state. Each of them can distinguish one state from other states. Leave-One-Subject-Out method was used to verify the performance of these three fisher classifiers. It means that each time we use 29 participants’ feature set as a training set, the remaining one participant’s feature set as test set to test classifiers’ classification performance. The test was repeated 30 times. The average confusion matrixes of these 3 classifiers are shown in Table 1 to Table 3

TABLE I. FISHER CLASSIFIER 1 FOR RELAXATION RECOGNITION

	Relaxation	**Other State**
Classified as Relaxation	97%	8%
Classified as Other State	3%	92%

TABLE II. FISHER CLASSIFIER 2 FOR PSYCHOLOGICAL STRESS RECOGNITION

	Psychological Stress	Other State
Classified as Psychological Stress	80%	8%
Classified as Other State	20%	92%

TABLE III. FISHER CLASSIFIER 3 FOR PHYSICAL STRESS RECOGNITION

	Physical Stress	Other State
Classified as Physical Stress	83%	2%
Classified as Other State	17%	98%

It is observed from Table 1 to Table 3 that the classification accuracy of three tests are all above 80%. The Psychological stress and physical stress can be recognized with 80% and 83% accuracy respectively. These results support that the stress can be recognized and that the psychological stress can be effectively discriminated from physical stress by using no-contact measured respiration signals.

IV. CONCLUSION AND DISCUSSION

We have presented a framework for detecting stress by using a Kinect sensor. The way of signal acquisition of Kinect characterizes the method a contact free stress detection method. The Kinect is small in size, light in weight, and affordable to ordinary users, which make the method suitable for continuous monitoring of human stress in everyday life.

The effect of physical stress when detecting psychological stress is considered in this research. When the context is unknown, the physical stress could be recognized as the psychological stress. By using features extracting from the respiration signal, we showed that the psychological stress can be differentiated from the physical stress.

Baseline information of every individual user will be required if a system based on the proposed framework is built and used for the psychological stress monitoring. This information could be recorded prior the use of the system and act as a calibration information within every individual's folder.

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