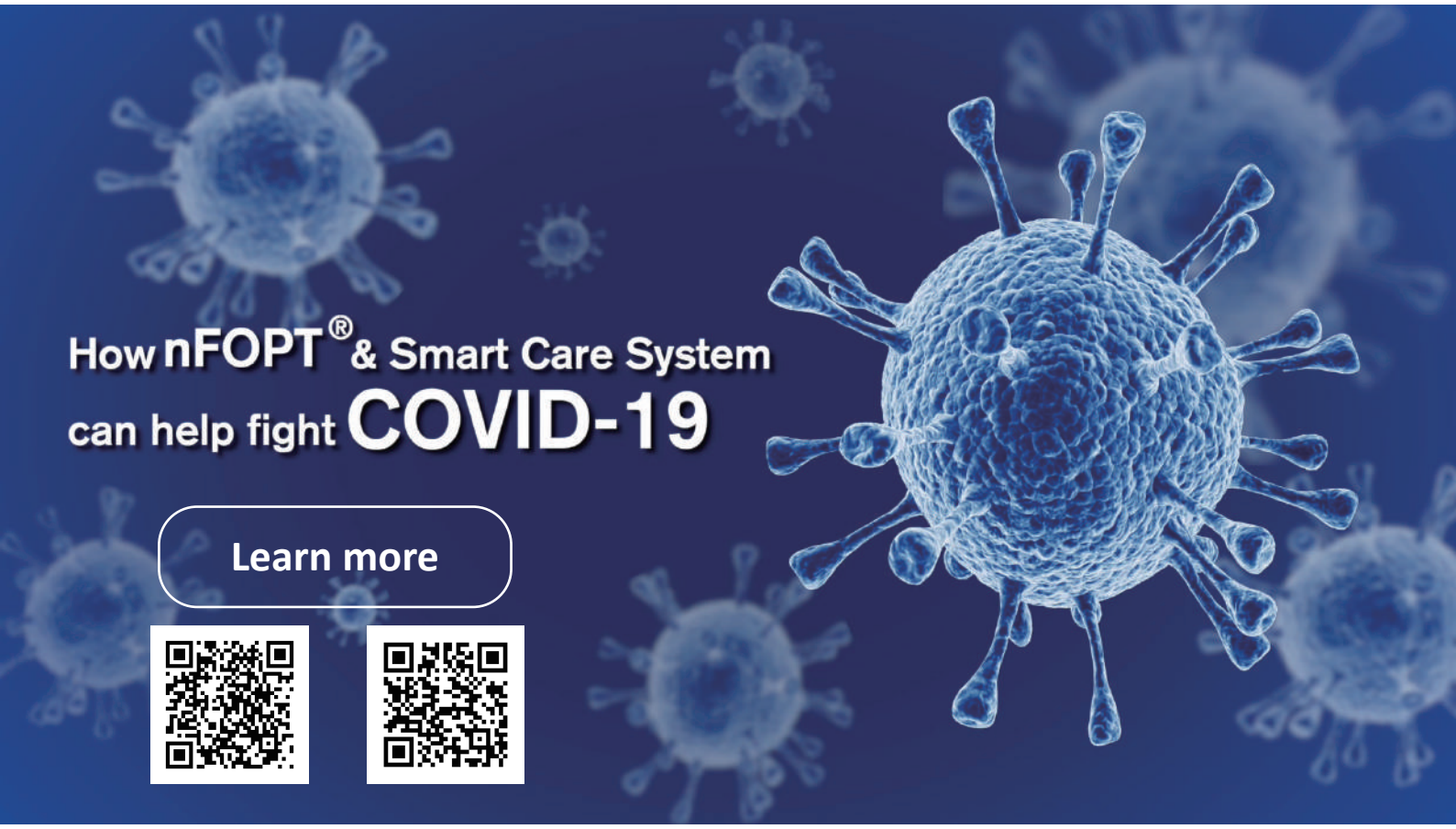
AI+nFOPT®

Non-invasive Fiber Optic Physiological Monitoring Technology

Effectively Tracking/Respiratory Symptoms/Persistent Coughing



- **Monitor Remotely**
  Smart Care System allows for reduced contact between infected and non-infected persons.
- **24 hour monitoring**
  which provides complete coverage of all patients simultaneously and puts less pressure and risk on medical staff.
- **Instantaneous alerts**
  The system detects changes immediately and alerts users instantaneously.
- **Waste Reduction**
  Reducing the contact of the medical staff also reduces the waste of medical.

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Research Summary

Sleep apnea assessment using declination duration-based global metrics from unobtrusive fiber optic sensors

Introduction

Sufficient sleep helps to restore the immune, nervous and cardiovascular systems, but is sometimes disturbed by sleep apnea (SA). The early diagnosis of sleep apnea is beneficial for the prevention of diseases. Polysomnography (PSG) recording provides comprehensive data for such assessment, but is not suitable for use at home due to discomfort during measurement and the difficulty of identification. This study proposes an unobtrusive measurement process by placing fiber optic sensors (FOSs) in a pillow (head-neck) or a bed mattress (thoracic-dorsal). We test two approaches: drop degrees from the baseline to validate the capability of catching respiratory drops, and linear regression models based on a new global measure, the percentage of the total duration of respiratory declination (PTDRD), to estimate the hand-scored apnea/hypopnea index (AHI). Based on data recorded from 63 adults, the drop degrees derived from respiratory signals exhibited statistical differences among central sleep apnea (CSA), obstructive sleep apnea (OSA) and normal breathing. The regression models based on the PTDRDs derived from head-neck FOS and thoracic-dorsal FOS also achieved good agreement with manually scored AHIs in Bland–Altman plots as well as oronasal airflow and thoracic wall movement. The aforementioned performance demonstrates the capability of the FOS measurement and the efficacy of the PTDRD metrics for SA assessment.

Materials and Methods

Two FOSs placed inside smart-care films are used to detect respiratory activity. As shown in figure 2, one flexible FOS film is embedded into a pillow to measure breath-induced vibrations that appeared on the head and neck. The other one is placed below a bed sheet near the dorsal thoracic region to detect thoracic wall movements.

This study was performed on 63 adults who came for clinical sleep examination at the Sleep Center in Cardinal Tien Hospital Yung Ho Branch. A PSG monitor was used to record oronasal airflow from the thermal sensors and nasal pressure sensor, thoracic and abdominal wall movements from respiratory inductive plethysmography (RIP), arterial blood oxygen saturation, electroencephalograms (F3, F4, C3, C4, O1 and O2), an electro-oculogram and electromyograms (left leg, right leg and chin). Simultaneously, respiration-induced head-neck and thorax vibrations were measured from FOS films inside the pillow and the bed sheet near the dorsal thoracic region. A sleep expert following the AASM criteria, identified SA and HYPO in the PSG data. Based on the analysis, their AHIs were calculated as the average number of respiratory events per hour of total sleep time. The subjects in different AHI groups show no significant differences in these data. This work adheres to the Declaration of Helsinki. The data collection and analysis were approved by the Human Subject Research Ethics Committee of Cardinal Tien Hospital (IRB# CTH-104-2-6-040). The participants gave their informed consent.

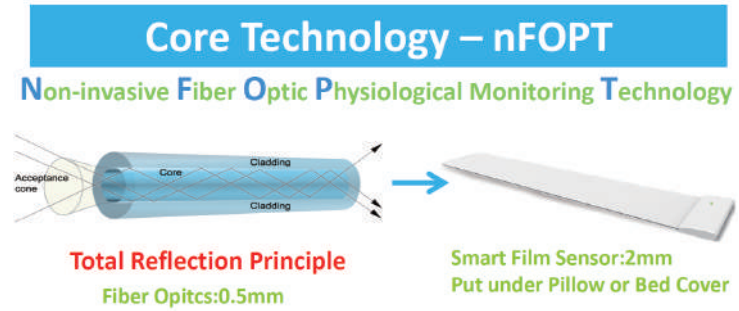

Figure 1. Non-invasive fiber optic physiological monitoring technology

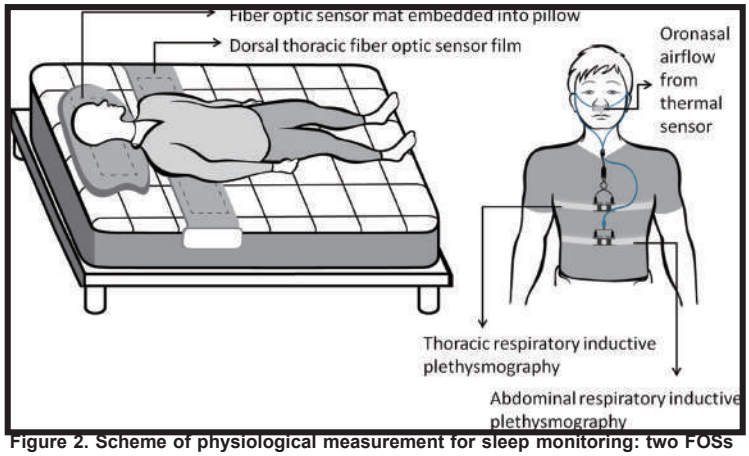

Figure 2. Scheme of physiological measurement for sleep monitoring: two FOSs are placed inside a pillow and under the subject's dorsal thoracic region, respectively. FOS deformations as well as oronasal airflow, thoracic and abdominal wall movements are recorded simultaneously in a PSG system.

Figure 3 shows the smoothed instantaneous respiratory intensity(IRI) of 5 min oronasal airflow, thoracic wall movement and head-neck/dorsal thoracic FOS deformations from three subjects with normal breathing, OSA and CSA. The IRI fluctuations are large and distinct in the cases with OSA and CSA.

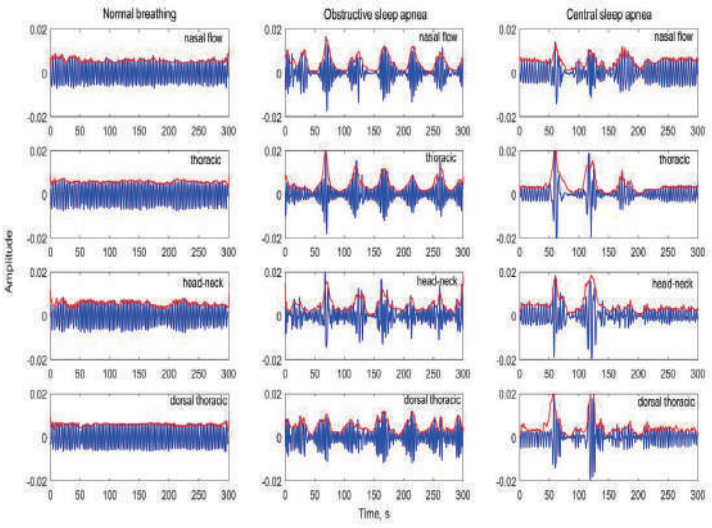

Figure 3. Oronasal airflow and respiratory effort derived from thoracic RIP and head-neck/dorsal thoracic FOSs (blue) and the computed IRI (red) during normal breathing, OSA and CSA

Results and Discussion

Evaluation of data from 63 subjects, the drop degrees associated with various respiratory events and normal breathing are listed in table 1.

Event	Nasal thermistor	Thoracic RIP	Head-neck FOS	Dorsal thoracic FOS
Central sleep apnea	79.3±0.1%	76.8±14.9%	66.6±16%	73.1±20.7%
Obtrusive sleep apnea	80.4±11.6%	39.6±21.8%	40.2±20.8%	27.3±22.3%
Hypopnea	37.6±15%	34.9±16.9%	24.9±17.5%	19.4±12.8%
Normal breathing	0.01±0.03%	0.01±0.04%	0.01±0.04%	0.01±0.05%

Table 1. Drop degrees associated with respiratory events and normal breathing

Measure	Regression equation	Correlation coefficient
Head-neck FOS	$AHI^* = 2.4266 \cdot PTDRD_1 + 1.5211$	0.7215
Dorsal thoracic FOS	$AHI^* = 2.2103 \cdot PTDRD_2 + 2.3827$	0.8487
Head-neck and dorsal thoracic FOS	$AHI^* = 0.7313 PTDRD_1 + 1.7964 \cdot PTDRD_2 + 0.8681$	0.8616
Oronasal thermistor	$AHI^* = 2.0301 \cdot PTDRD_3 + 5.0245$	0.8657
Thoracic RIP	$AHI^* = 2.0252 \cdot PTDRD_4 + 2.0132$	0.8436
Oronasal thermistor and thoracic RIP	$AHI^* = 1.2436 \cdot PTDRD_3 + 0.9724 \cdot PTDRD_4 + 3.2726$	0.8954

Table 2. Regression models for estimating the AHI* using PTDRD

PTDRD1, PTDRD2, PTDRD3 and PTDRD4 represent the PTDRDs derived from the respiratory signals of the head-neck FOS, dorsal thoracic FOS, oronasal thermistor and thoracic RIP, respectively. The relationship between the PTDRDs and the manually scored AHI is indicated by the Pearson correlation coefficient.

Conclusions

FOS has been demonstrated as being useful to detect SA as well as traditional PSG, it can help early screening of possible respiratory disorders in a non-hospital environment. FOS will be suitable for home screening and guidance for further examinations. Moreover, the new global metric, PTDRDs, expresses the frequency of respiratory events by the percentage of durations in respiratory declinations, without critical criteria to detect SA and hypopnea. The PTDRD derived from oronasal airflow, thoracic RIP, head-neck FOS, dorsal thoracic FOS or their combinations can be a potential indicator for assessing SA syndrome.

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Research Summary

Source: The 8th International Symposium on InfoComm & Mechatronics Technology in Bio-Medical and Healthcare Applications 2018 November 21-24

Deep CONVOLUTIONAL NEURAL NETWORK FOR SLEEP STAGE CLASSIFICATION

Introduction

Humans spend roughly one-third of their lives asleep. Good quality and sufficient sleep are crucial for all the people. According to the report of the American Sleep Association, there are about 50-70 million US adults who suffer from a sleep disorder such as insomnia, sleep apnea, restless leg syndrome, etc. In past decades, automatic sleep stage scoring almost depended on feature extraction based methods by human intelligence. With the rapid development of artificial intelligence over the last several years, many new deep learning relative models had been utilized in medical field. It overcomes the limitation of the feature extraction techniques and achieved a remarkable accuracy for sleep stage scoring. In clinical sleep examination, polysomnography (PSG) is considered as gold standard equipment which can provide comprehensive bio-signals for sleep quality assessment and sleep breathing-related disorder diagnosis. Identification of apnea/hypopnea events and sleep stage classification is usually performed by sleep expert with computer-assisted sleep scoring system. Undoubtedly, this is an extremely time-consuming work. To develop an automatic sleep stage scoring system to aid physician to diagnose sleep disorders is necessary. Recently, a number of researches focus on automatic sleep stage classification based on Electroencephalography (EEG) had been proposed. But, sleep stages classification for patients with different degree of sleep apnea severity is less addressed in literature. There are various frequencies of sleep EEG signals and artifacts caused by arousal. Typical methods for sleep stage classification cannot distinguish these variations. We also found that using single filter size of proposed CNN is not appropriate for sleep stage scoring in subjects with different severity of sleep apnea. In particular, the sleep stage classification for those subjects who have moderate or severe sleep apnea. Once an apnea event occurred, higher amplitude and frequency artifacts or awake-related components may appear in EEG signals. This variation may lead to a misclassification.

Materials and Methods

The number of enrolled subjects is 43 adults who came for PSG examination at the Sleep Center in Cardinal Tien Hospital Yung Ho Branch. The whole-night EEGs of each subject were divided into consecutive 30-s epochs. In total, 32975 epochs are available from these 43 subjects. And their demographic data of the subjects are listed in Table 1. Electroencephalograms (F3, F4, C3, C4, O1, and O2 by the International 10-20 EEG system), and relative physiological signals were simultaneously recorded by a polysomnography monitor with a sampling rate of 200 Hz (The Philips Alice 6 LDX PSG System, Philips Electronics, Inc., Amsterdam, Netherlands). The data collection and analysis was approved by the Human Subject Research Ethics Committee of Cardinal Tien Hospital (IRB# CTH-104-2-6-040).

	Number of subjects	Gender(M/F)	Age(years)	BMI(kg/m²)
AHI<5	16	12/4	47.5±14.9	22.9±3.1
5≤ AHI<15	15	7/8	44.5 ±12	26.7±3.9
AHI ≥15	12	12/0	42±11.3	28.3±4.1
Overall	43	31/12	44.93±12.9	25.8±4.3

Table 1. Group categorized by apnea hypopnea index(AHI); data expressed in terms of mean ± standard deviation

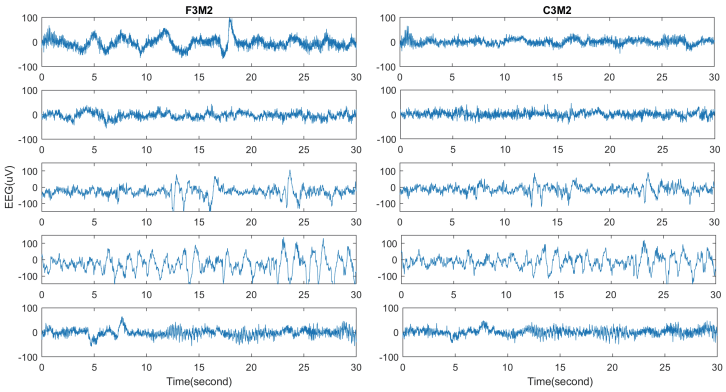

Figure 1. The EEG signals at F3 and C3 electrode in wake, N1, N2, N3 and REM stages.

The new model in this study was composed of three parallel CNNs extended from a deep CNN resembled the LeNet-5 and AlexNet. Each CNN consists of two convolutional layers, two max-pooling layers, two Local Response Normalization (LRN) layers, two drop out layers, one stacking layer, one fully connection layer, and softmax layer. In order to consider both temporal and frequency precision, the different size of filters at the first layer of each CNN was adopted.The architecture of proposed CNN model was illustrated in Figure 2.

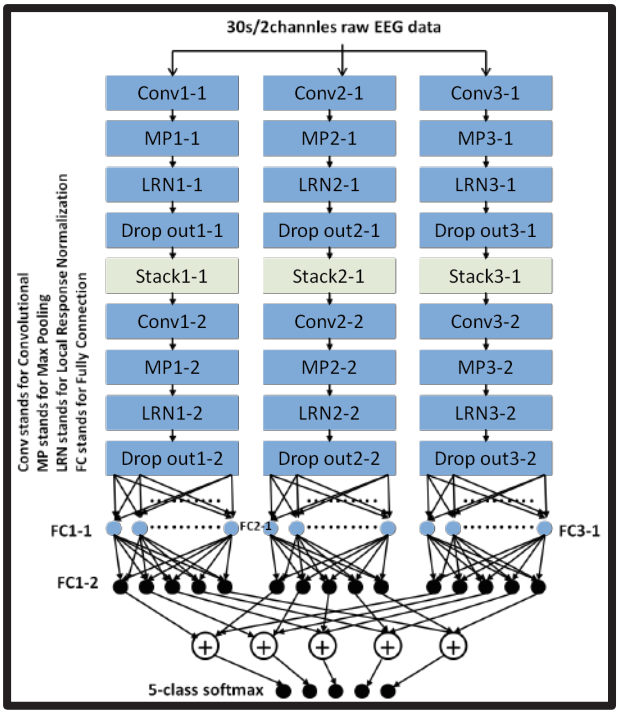

Figure 2. CNN Architecture

Results and Discussion

Evaluation of data from 43 subjects, we achieved overall 82.5% accuracy for sleep stage scoring in all subjects with different severity of sleep apnea. In particular, the sleep stage classification for those subjects who have moderate or severe sleep apnea. Once an apnea event occurred, higher amplitude and frequency artifacts or awake-related components may appear in EEG signals. This variation may lead to a misclassification. We proposed an new CNN model to this overcome this issue. For normal subjects, mild sleep apnea subjects, and moderate and severe subjects, the classification accuracy is 82.8%, 82.8%, and 81.9% respectively.

CNN Model

Sleep expert	Wake	NREM1	NREM2	NREM3	REM	Total	Precision	Recall	F1-score
Wake	4746	62	37	1	88	4934	75.7%	96.2%	0.847
NREM1	479	1706	737	0	524	3446	53.5%	49.5%	0.5142
NREM2	347	1039	14459	417	619	16881	92.9%	85.7%	0.8915
NREM3	0	0	82	1108	0	1190	72.6%	93.1%	0.8159
REM	701	382	242	0	5199	6524	80.9%	79.7%	0.8027
Total	6273	3189	15557	1526	6430	32975			

Table 2. Confusion matrix for all 43 subjects including normal individuals and subjects with sleep apnea (accuracy is 82.5% and Kappa is 0.743)

Conclusions

The standard sleep stage classification specified by the AASM manual requires at least 3 channels of EEG to cover frontal, central and occipital brain areas, respectively. Recently, a number of researches attempted to use single-channel EEG for sleep stage scoring by deep learning and achieved over 80% accuracy. Two-channel EEGs measured at frontal and central lobes were utilized in this study for comfortable measurement.

In previous, some studies have shown that the agreement rate in sleep stage classification is less than 90% among sleep experts. Evaluation of data from 43 subjects, we achieved overall 82.5% accuracy. Since subjects with sleep apnea symptom, once apnea occurred, it accompanied with more high amplitude and frequency artifacts in EEG signals. Thus, typical methods for sleep stage classification cannot distinguish this variation and lead to misclassification easily. In this study, the proposed CNN model adopted tree CNN with different size of filters that is suitable for sleep stage scoring in all subjects with a different degree of sleep apnea severity. To design an unobtrusive measurement device with artificial intelligence for home environment monitoring is our future work.

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Research Summary

Vital sign monitoring using fiber-optic sensor

Introduction

Fiber optic sensors (FOSs) have gained increasing applications in various physical measurements, such as strain, temperature, displacement ,and pressure. Based on previous studies, FOS also has been demonstrated to work as well in monitoring vital signs. Recently, unobtrusive sensing devices for vital signs have become a mainstream application. With this advantage, it can help early screening of possible heart or respiratory diseases in a non-hospital environment. Also, FOS has been demonstrated as being useful to monitor heart rate and respiratory rate as well as traditional sensors such as electrocardiogram electrode and respiratory inductive plethysmography. FOS will be suitable for home screening and guidance for further examinations.

To validate the feasibility of the FOS, an oronasal airflow sensor and ECG are employed in capturing respiratory, and heartbeat vibrations as well for comparison. The FOS placed inside the smart-care film is used to detect heart and respiratory activity. As shown in figure 2, the flexible FOS film is embedded into a pillow to measure breath induced vibrations that appeared on the head and neck and the subtle cardiogenic body movement once heart ejects blood into the arteries.

Figure 1. smart-care film and system

Materials and Methods

The number of enrolled subjects is 63 adults who came for PSG examination at the Sleep Center in Cardinal Tien Hospital Yung Ho Branch. Electrocardiogram and respiratory signals and another relative physiological signals were simultaneously recorded by a polysomnography monitor with a sampling rate of 200 Hz The data collection and analysis was approved by the Human Subject Research Ethics Committee of Cardinal Tien Hospital (IRB# CTH-104-2-6-040).

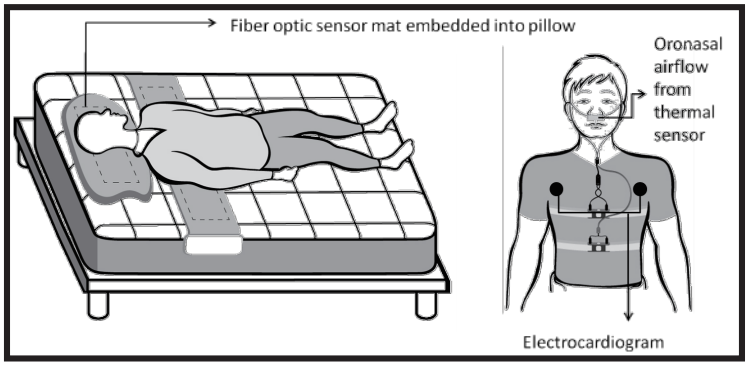

Figure 2. Scheme of physiological measurement for sleep monitoring: one FOS is placed inside a pillow. ECG, FOS deformations and oronasal airflow are recorded simultaneously in a PSG system.

Once heart ejects blood into the arteries and the subtle cardiogenic body movement can be measured using high sensitivity sensors. This variation we call it “ballistocardiogram”. The first BCG research was published in 1877 and following Isaac Starr designed a new type of bed BCG measurement device that can be considered as a modern ballistocardiography measurement in 1936. Recently, various types of bed and chair type BCG measurement devices have been developed.

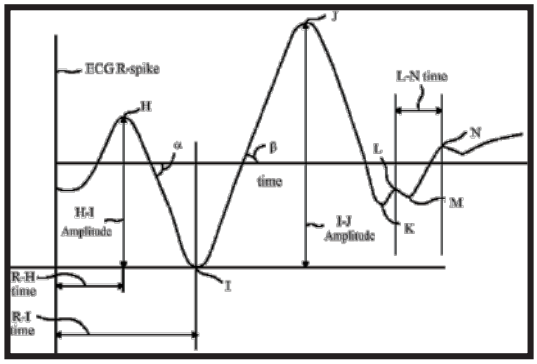

Figure 3. A theoretical BCG waveform and its components. The extrema of the BCG waveform are denoted with F, G, H, I, J, K, L, M, and N. The R-spike of the ECG can give timing reference.[1]

Respiration-induced head-neck vibrations were measured from FOS film inside the pillow. Simultaneously, subtle cardiogenic body movement (ballistocardiogram) can be recorded as well. The airflow from the oronasal thermistor, the respiratory effort from the head-neck respiratory signals from FOS films and extracted BCG were adopted for analysis. Four real measured physiological signals as shown in figure 4. these signals can demonstrate the feasibility of fiber optic sensor.

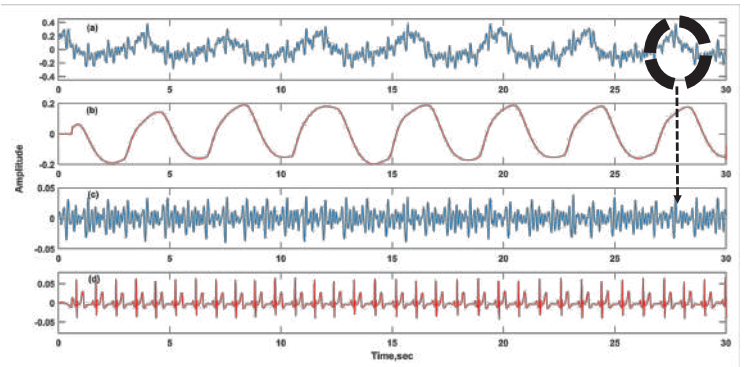

Figure 4. Four real measured physiological signals to demonstrate the feasibility of fiber optic sensor (a) respiratory signal from FOS (b) respiratory signal from temperature flow sensor (c) cardiogenic body movement (BCG) extracted from signal(a) (d) lead one ECG

Results and Discussion

Evaluation of data from 8 subjects, the mean absolute error(MAE) of all subjects for the average beats/breaths per minute computed during the sleep testing(overnight). Averaged across the 8 subjects, the MAE error was 0.51 ± 0.47 bpm and 1.07 ± 0.49 bpm for the mean respiratory rate and mean heart rate as shown in table 1 and table 2 respectively.

Mean Breath Rate(breaths/min)			
Sensor / Subject	*Oronasal flow*	*FOS(Respiratory)*	Absolute error
1	12.99±1.21	14.13±1.52	1.14
2	16.1±1.9	16.31±1.66	0.21
3	14.39±1.23	14.37±1.32	0.02
4	13.33±1.44	13.63±1.38	0.3
5	14.21±1.11	14.54±1.39	0.33
6	13.21±1.1	14.5±1.8	1.29
7	13.67±1.09	14.31±1.31	0.64
8	13.56±1.42	13.71±1.45	0.15
Total			0.51±0.47

Table 1. Respiratory rate derived from oronasal airflow and head-neck FOS. The values expressed by mean ± standard deviation

Mean Heart Rate(beats/min)			
Sensor / Subject	*ECG*	*FOS(BCG)*	Absolute error
1	60.35±6.15	61.02±5.05	0.67
2	66.72±2.41	65.85±2.04	0.87
3	65.93±5.56	63.84±4.06	2.09
4	67.59±7.68	66.18±5.86	1.41
5	67.23±7.49	65.99±5.25	1.24
6	61.2±2.89	62.19±2.92	0.99
7	57.62±5.81	58.24±3.65	0.62
8	50.74±4.29	51.48±2.83	0.74
Total			1.07±0.49

Table 2. Heart rate derived from ECG and head-neck FOS (BCG). The values expressed by mean ± standard deviation

Conclusions

Electrocardiogram (ECG) has been widely used in clinical diagnosis of cardiovascular diseases. But it is not convenient for long-time heart activity monitoring and traditional respiratory sensors also have this disadvantage. To design an unobtrusive measurement device with artificial intelligence for home environment monitoring is necessary. We have developed an unobtrusive sensor with the proprietary non-invasive fiber optic physiological monitoring technology and achieved the heart/breath rate measurement as accurate as ECG/oronasal airflow sensor. The high sensitivity, high precision, and accuracy of the fiber optic sensor can be applied to babies and elderly home/institutional care and has been used in hospitals over several years. nFOPT can monitor sleep safety and health with no wearable devices, no electromagnetic wave, with high safety and accuracy. It can also combine with IoT functions and it responds to movements of the baby and elderly. It’s unique simple movement learning system provides elderly with a better quality of life and their dignity.

The application includes smart pillow; mat; mattress; smart clothes; smart care room and smart care system. The best solution is Smart Care System that monitors and manages multiple beds or rooms in a cost-effective way and helps to resolve the shortage of caregivers problem by providing 24/7 auto rounds and allows care recipients an ability to receive quality care with dignity.

Reference

[1] https://www.cs.tut.fi/sgn/SSSAG/BCG.htm