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Classification of Sleep-Wake State in Ballistocardiogram system based on Deep Learning *

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***Abstract*— Sleep state classification is essential for managing and comprehending sleep patterns, and it is usually the first step in identifying sleep disorders. Polysomnography (PSG), the gold standard, is intrusive and inconvenient for regular/long-term sleep monitoring. Many sleep-monitoring techniques have recently seen a resurgence as a result of the rise of neural networks and advanced computing. Ballistocardiography (BCG) is an example of such a technique , in which vitals are monitored in a contactless and unobtrusive manner by measuring the body's reaction to cardiac ejection forces. A Multi-Headed Deep Neural Network is proposed in this study to accurately classify sleep-wake state and predict sleep-wake time using BCG sensors. This method achieves a 95.5% sleep-wake classification score. Two studies were conducted in a controlled and uncontrolled environment to assess the accuracy of sleep-awake time prediction. Sleep-awake time prediction achieved an accuracy score of 94.16% in a controlled environment on 115 subjects and 94.90% in an uncontrolled environment on 350 subjects. The high accuracy and contactless nature make this proposed system a convenient method for long-term monitoring of sleep states, and it may also aid in identifying sleep stages and other sleep-related disorders.**

***Clinical Relevance*— Current sleep-wake state classification methods, such as actigraphy and polysomnography, necessitate patient contact and a high level of patient compliance. The proposed BCG method was found to be comparable to the gold standard PSG and most wearable actigraphy techniques, and also represents an effective method of contactless sleep monitoring. As a result, clinicians can use it to easily screen for sleep disorders such as dyssomnia and sleep apnea, even from the comfort of one's own home.**

***Index Terms*— 1D-Convolutional Neural Networks, Ballistocardiogram, Multi-Head Networks, Non-invasive monitoring, Sleep State Detection**

I. Introduction

Sleep-state detection refers to identifying sleep and non-sleep episodes for a subject. Estimating sleep states is an initial and primary step in analysing and addressing more serious sleep disorders. In the general population, the majority of sleep disorders go undiagnosed. [1]. Many of these sleep disorders are detectable through sleep state estimation [2]. Although polysomnography (PSG) is the current gold standard in high-resolution sleep monitoring, it is obtrusive, costly, and requires recording in an unfamiliar and controlled setting [3]. Individuals must spend the night in a sleep laboratory, which is a controlled environment where they are constantly monitored by a sleep technician. For decades, techniques for generating fresh solutions for effective sleep-state estimation have been a primary emphasis in sleep medicine [4]. Researchers have begun investigating wearables for detecting sleep-state with the rise of computational efficiencies [5]. Though these devices are simpler to operate than a PSG, [6] they are susceptible to errors and lack essential confirmation, such as device settings standardisation. In addition, they need to be worn all the time, which can be uncomfortable, making continuous monitoring difficult.

Non-contact ballistocardiography (BCG) is a non-invasive method of assessing cardiovascular functions. Ballistocardiography, unlike PSG, does not require the attachment of external electrodes and or direct contact with a subject, thereby avoiding patient discomfort. This system is ideal for discrete long-term continuous data monitoring [7,8]. It can also be used in almost any sleep setting (including the subject's own bed at home), not just a hospital sleep lab.

This paper proposes an efficient and contactless method based on BCG and deep learning to monitor sleep states. The sleep-awake time is calculated using a multi-head 1D-CNN architecture and a prediction algorithm for sleep state classification. Two independent studies were conducted in a controlled and an uncontrolled setting to assess the accuracy of sleep and wake-up time prediction.

II. Methodology

A. Data

1) BCG Data Acquisition

Dozee [7,8], a contactless sleep and vitals monitoring device, is used to collect BCG data. A mesh of Polyvinylidene fluoride-based vibroacoustic sensors is placed beneath the mattress to capture micro and macro-vibrations produced by the body while lying over the sensor array, which is linked to a data-acquisition unit that samples vibrations at a frequency

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of 250Hz. The five features used in this study are heart rate, difference in successive heartbeat intervals, heart rate confidence interval (confidence of calculated heart rate), breath rate, and movements, as these parameters have shown a significant influence in the prediction of a subject's sleep and wake up time. BCG data was collected from 600 subjects at their homes (uncontrolled setting) and 115 subjects in a sleep lab (controlled setting). Recordings on subjects were made in accordance with the Declaration of Helsinki, and all subjects provided informed consent.

B. *Sleep-State Classification*

1) *Pre-Processing*

The BCG data is sampled such that a value for each epoch (30s) is obtained. Heart rate and breathing rate is calculated using the algorithms mentioned in [7,8]. Movement is measured using the algorithm mentioned in [9]. A confidence parameter was created for heart rate using the correlation between the selected cluster and its base template, while heart rate difference is the difference between the $(n+1)^{th}$ epoch heart rate to nth epoch heart rate.

2) *1D Convolutional Neural Networks (CNNs)*

On the time series data, 1D CNNs were used. The BCG data is sampled in such a way that a value for each epoch (30s) is obtained, as shown in Fig. 1. 15-minute (30-epoch) windows are used as input to determine whether the 15th minute is asleep or awake. The prediction was made using a rolling window of 15 minutes (30 epochs) separated by 1-minute intervals (2 epochs). Over the data available from BCG sensors, the prediction algorithm was performed on categorization scores to identify the likely sleep and wake-up time. Over the data available from BCG sensors, the prediction algorithm was performed on categorization scores to identify the likely sleep and wake-up time. This was done during the whole period when data from BCG sensors was accessible, and forecasts were made in real time. A feature detector sliding from the start position to the end position in the 1D CNN technique, extracts deep features at each instance (Fig. 2). The breadth of the feature detector indicates the resolution with which it scans the whole 15-minute (30 epoch) going from left to right. The detector width in Fig. 3 is 6 epochs or 3 minutes long, implying that the first feature extraction occurs from all feature values between t_1 and t_3, the second from t_2-t_4, and so on until t_{28}-t_{30}.

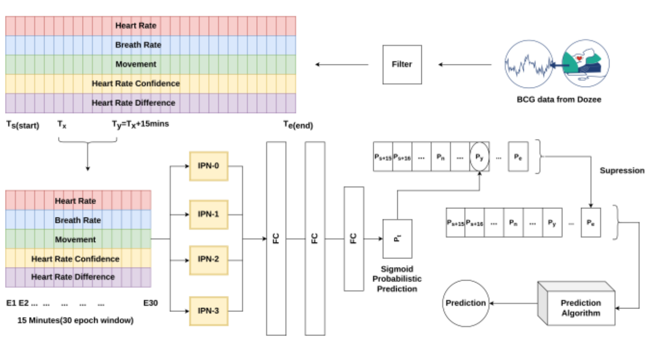

Fig. 1: The algorithm's complete flow

3) *Multi Head Network*

The standard 1D CNN neural network is rigid and only captures features at a specific resolution. Because there is a strong relationship between signal amplitudes at different time instances and the sleep-state, a 15-minute window with different time resolutions. This helps in making prediction based on combined information obtained from sliding the window at different resolutions.

We thus used, four different heads, each of which was processed at a resolution of 3, 5, 7, and 11 epochs. To create intermediate predictions, these 1D convolutional features are passed on to an intermediate fully connected (FC) layer. To avoid data overfitting, low-level max-pooling, batch normalisation, and apply dropouts were performed before transferring the data to the FC layers. After intermediate FC layer processing, the four intermediate predictions correspond to predictions generated at four distinct resolutions. These intermediate predictions are combined and transmitted to a simple shallow fully connected network, which produces a probabilistic binary prediction as its output. Fig. 3. depicts the overall architecture.

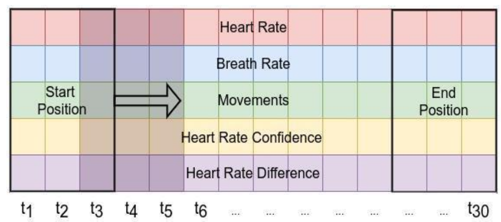

Fig. 2. 1D Convolution Based Feature Extraction

4) *Prediction Algorithm*

The output of Multi-Head CNN is obtained as the probability of sleep and awake state on a rolling basis. This information is fed into the prediction algorithm, which is the final step in determining sleep and wake-up times. The prediction probability array is initially fed via a 1D Non-Max Suppression algorithm, which helps forecast by removing any tiny period of sleep-state changes. If at least 45 minutes of sleep are seen following the probable sleep time timestamp with no more than 10 minutes of continuous awake predictions, the probable sleep time timestamp is deemed sleep time. Similarly, if at least a 15-min period of awake prediction is detected before the potential wake-up timestamp, it is deemed to be a wake-up time. The result of this procedure forecasts the eventual sleep and wake-up timings.

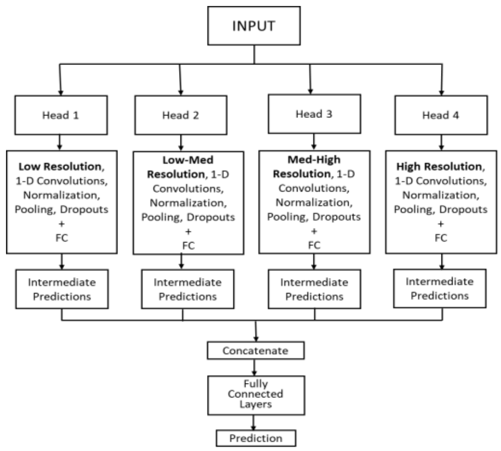

Fig. 3. Multi-Head Classification Network

5) *Transfer Learning*

The approach has a low margin of error, which can be lowered by using transfer learning. Transfer learning is the process of improving learning in a new activity by transferring information from a previously acquired related task [11]. Because vitals change from person to person, it is challenging to generalise a similar deep learning model for all individuals. As a consequence, an expanded transfer learning module for persons with diverse sleep habits is presented. For example, a group of patients suffering from periodic limb movement disorder are constantly fidgeting in their sleep, and so on.

III. Results

A. *Evaluation Method*

BCG data from 250 of the 600 subjects in an uncontrolled environment, amounting to an average of 6.5 hours of data per user, was used for training. This data was then annotated based on participant feedback and divided into multiple 15-minute sleep and awake windows. 100,000 15-minute sleep and awake windows were created for use as input to the deep learning architecture. The data an hour before and an hour after the sleep-state shift was evaluated from the entire data available for an individual. The outcomes are the average scores received after 10 separate runs. The first step in this method is to classify the 15-minute window as a sleep or awake window on a one-minute roll for the entire duration of data. Before arriving at multi-Head 1D convolutions, several alternative algorithms were tested with the objective of attaining maximum accuracy in categorising the 15-minute timeframe. Because classification accuracy has a significant impact on the final outcome (sleep-wake time), this first step is critical. The scores were calculated by categorising 20,000 15-minute windows as sleeping or awake.

Model-1 (with a 95.5% classification score) proved to be the most efficient and accurate. Two procedures were used to test the method. First, tests were performed on subjects in a controlled environment using PSG verification, and then the method was extended to an uncontrolled setting. Both of these evaluation procedures demonstrated that our method is consistent with PSG methodology and that it is suitable even in an uncontrolled (normal) environment such as at home

B. *Evaluation-1 Controlled Environment*

The method was scored in this evaluation based on medical data gathered from PSG of 115 subjects. All recordings were done using a Nihon Kohden Neurofax EEG-1200 machine (24-bit resolution, 1024 Hz sampling rate, and 0.1-250 Hz bandpass filter) and 24 electrodes as per American Academy of Sleep Medicine [11] guidelines. Our method's accuracy, precision, specificity, and sensitivity were calculated against the manual tagging done on PSG data by an expert. Table I contains a summary of the results. A classification accuracy of 92.6% in a 15-minute window was achieved, which surpassed existing actigraphy-based techniques [11].

TABLE I. STATE CLASSIFICATION (CONTROLLED)

Measure	Value
Accuracy	92.63%
Precision	95.80%
Specificity	95.49%
Sensitivity	90.12%

This method was then graded based on the timestamps of sleep and waking up. A 15-minute relaxation period between the actual and predicted times was used. The results are summarised in Table II.

TABLE II. SLEEP-AWAKE TIME PREDICTION

Measure	Controlled	Uncontrolled
Accuracy	94.16%	94.90%
Precision	97.32%	96.04%
Specificity	97.14%	96.13%
Sensitivity	91.53%	93.67%

C. *Evaluation-2 Uncontrolled Environment*

Tests were performed on the remaining 350 subjects in the uncontrolled environment. In this evaluation, the method was scored against the ground truths for sleep and wake up time based on user feedback. Subjects were tested on multiple random days, yielding a total of 1500 samples with an average of 7 hours of data per sample. Table III displays the final results.

D. Transfer Learning

Samples from 5 random days were gathered for each user whose sleep or wake up time was inaccurate in order to perform transfer learning on the original architecture. We gathered samples 10 days apart from the training samples for testing, and accuracy was assessed using both our base architecture and the transfer learning technique. When compared to the baseline model, the new transfer learning-based model improved accuracy by 22 percent on average. Furthermore, a maximum rise of 40% was reported in the new model. This illustrates that, when applied on a broader scale, this method can minimise error even more.

IV. Discussion

Determining the subject's clinical awakeness is one of the most crucial procedures before analysing sleep-related diseases. Even in long-term healthcare monitoring, sleep patterns can provide useful information about a person's health and mental well-being. As a result, many researchers are interested in the topic of sleep awake classification and multiple technologies have been developed. However, most of them disrupt natural sleeping patterns by incorporating monitoring methods that are intrusive, uncomfortable, and impractical for daily use. The need of the hour is a system that is appropriate for non-intrusive continuous data acquisition which can be used in any setting whether home or hospital. BCG in combination with deep learning techniques could be the ideal system for sleep studies.

The proposed MH 1D CNN based network method was tested on 115 subjects in controlled conditions and 350 subjects in uncontrolled conditions. The higher scores obtained in the sleep state classification and in sleep-wake time prediction in both controlled and non-controlled settings demonstrates this method's efficacy and that it is suitable even in an uncontrolled (normal) environment such as at home. The method produces sensitivity, specificity, and precision scores comparable to the gold standard PSG techniques as well as higher than most wearable actigraphy techniques [2]. The wearable actigraphy devices currently in use are typically based only on accelerometry and cannot be reliably used as a diagnostic tool in clinical settings [11]. Moreover, the devices require a higher level of compliance compared to contactless methods and are inconvenient to sleep with.

Unlike this study, most sleep-awake detection studies are conducted on a small number of subjects in a medically controlled environment, highlighting the robustness of this approach. This study's method is novel because it uses a contactless technique with high accuracy. This study's sleep parameters can also be used to calculate total sleep duration, the number of times a subject wakes up while sleeping, and sleep quality. This method can be extended to assess insomnia, excessive daytime somnolence, sleep apnea and respiratory disturbances, sleep in psychiatric and other medical conditions, sleep patterns and their effects.

V. Conclusion

In this study, a deep learning-based multi-head architecture for sleep-awake state classification was proposed and extended for sleep time and wake up time prediction using the proposed prediction algorithm. Furthermore, the opportunities for transfer learning for long-term use cases were investigated. The obtained results are comparable to other contact-based actigraphy techniques, making our proposed non-contact approach preferable to existing methods. In the future, this research could be expanded to include sleep stage classification and the study of various sleep disorders. Because of the demonstrated high accuracy and efficiency, this method is a strong contender for use in hyper-scaled uncontrolled settings and has the potential to be used in healthcare products to monitor sleep quality over a long term for virtually any subject. Further clinical validation of accuracy is required through controlled trials.

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