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Sleep-Awake Detection  
Using Non-Contact  
Ballistocardiogram System

# Multi-Head 1D CNNs For Sleep-Awake Detection Using Non-Contact Ballistocardiogram System

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Sleep-Awake or sleep-state detection refers to identifying sleep and non-sleep episodes for a subject. Sleep-state estimation is one of the first steps in analyzing and approaching solutions to more serious sleep disorders. Most sleep disorders remain largely undiagnosed in the general population [1]. Many of these sleep disorders can be identified using sleep state estimation [2]. Techniques to build novel solutions for efficient estimation of sleep-state have been one of the important topics of focus for the past few decades [3]. Today researchers are leveraging the high computing power and modern AI-based techniques to achieve better results. Earlier researches focused on traditional techniques such as Polysomnography (PSG) which is regarded as the current gold standard in high-resolution sleep monitoring, but the method is expensive and recordings are performed in an unfamiliar and controlled environment. With the rise of computational efficiencies, researchers started exploring wearables for detecting sleep-state. Techniques such as Wrist Actigraphy (WA) [8] where devices worn around the wrist record movements that can be used to estimate sleep parameters with specialized algorithms were introduced to compute total sleep time, efficiency, and intermediate awakenings. These devices are easy to use as compared to burdensome PSG which employs electrodes to measure brain dynamics of EEG, eye movements, muscle activity, heart physiology, and respiratory function [8]. However, as compared with PSG, actigraphy is known to overestimate sleep and underestimate the awake time and is known to lack critical confirmation including standardization for device settings. The device can be uncomfortable when worn all the time making continuously monitoring difficult. In this study, we propose an efficient contactless sleep-state monitoring using ballistocardiography (BCG) and deep learning. Non-contact BCG is an unobtrusive and non-invasive system that evaluates cardiovascular functions without any difficulty. In comparison to PSG, BCG does not require external physical electrodes to be connected and avoids any direct contact with a subject, avoiding any uneasiness

and discomfort. Such a system is suitable for long-term continuous data acquisition.

With the rise of computing power, there have been tremendous advances in the field of Artificial Intelligence (AI). These tools may improve prognosis, diagnostics, and care planning and it is believed that AI will be an integral part of healthcare services in the near future. In this study, we focus on deep learning [7] based on Convolutional Neural Networks (CNN) which have come to be recognized as prominent feature extractors. For medicine in general, CNNs have enabled Computer-Aided Diagnosis to occasionally outperform experts [6]. We use multi-head 1D-CNN architecture to classify the sleep state and a prediction algorithm is run to obtain sleep and wake-up time. We also discuss the real-time implementation of this approach along with the integration of transfer learning for long term stability.

## METHODOLOGY

We use Dozee [4,5], a contactless sleep and body vitals monitoring device (shown in Fig 1), for acquiring BCG data. The system is placed under the mattress to capture micro and macro-vibrations generated by the body which includes cardiac contractions, breathing, body movements, snoring when lying over the sensor array is attached to a data-acquisition unit sampling vibrations at a rate of 250Hz. We used Heart Rate, Breath Rate, Heart Rate Confidence Interval (confidence of calculated heart rate), Movements, and the difference in successive heartbeat intervals as five prominent features in this study. These parameters have shown a great influence in the prediction of sleep time and wake up time of a subject.



Fig 1. Dozee in use

We then process the signals and feed it to a 1D-CNN based network with multi-head structure processing features at different resolutions. The model has been evaluated in both controlled (medical) and uncontrolled environments.

## RESULTS

We achieve good performance in both environments which proves the robustness of the method introduced, The results are based on efficiency to detect the sleep time and wake up time with a relaxation of 15 minutes.

Table I. Sleep time Wake time prediction(controlled)

Measure	Value
Accuracy	94.16%
Precision	97.32%
Specificity	97.14%
Sensitivity	91.53%

Table II. Sleep time Wake up time prediction (Uncontrolled)

Measure	Value
Accuracy	94.90%
Precision	96.04%
Specificity	96.13%
Sensitivity	93.67%

Table I shows the scores for our tests in a medically controlled environment and Tabel II shows the scores in an uncontrolled environment. The ground truth for both the tests was the recordings from PSG techniques and feedback from our subjects. Most of the studies around sleep awake detection have focused on a small study group in a medically controlled environment. The contactless technique with good accuracy, evaluation, and generalization makes our method novel. This method can be further extended to:

- Assessment of insomnia and excessive daytime somnolence
- Assessment of sleep apnea and respiratory disturbances
- Assessment of transient and chronic schedule disorders
- Sleep in psychiatric and other medical conditions

- Assessment of medical interventions-drug studies

## CONCLUSION


In this study, we built a deep learning-based multi-head architecture for the classification of sleep-wake state and we extend it to sleep time wake up time prediction using our proposed prediction algorithm. We further explore the opportunities around transfer learning for long term use cases. The results obtained are at-par with other contact-based actigraphy techniques which makes our proposed non-contact approach desirable as compared to existing methods [3, 9]. This study can be further extended to sleep stage classification in future research.

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