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Research Article

Improving Heart Rate Monitoring During Sleep Through Trunk Muscle Artifact Separation from ECG Signals

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ABSTRACT

Monitoring heart rate (HR) during sleep is a crucial method for detecting early signs of cardiac and sleep disorders. But regular heart rate monitors and accelerometers often have trouble telling the difference between normal changes in heart rate and changes that happen when you move or use your muscles. This paper proposes a method to isolate trunk muscle signals (ECG-TMS) from ECG recordings to address this issue. This method utilises the discrete wavelet transform (DWT) to get rid of artifacts caused by muscles, which makes heart rate readings more accurate. A controlled experiment involving a healthy adult male was executed using Shimmer3 ECG equipment to gather data in simulated sleep environments. The method of ECG-TMS did a great job of getting clean heart signals, which made the signal-to-noise ratio (SNR) much better and made it possible to reliably find the heart rate even when the body moved a little. This method was better at getting rid of noise and picking up small muscle movements than systems that used accelerometers. These findings suggest that ECG-TMS may be particularly beneficial in sleep research, cardiovascular diagnostics, and wearable monitoring technologies. Further research will aim to validate the system in real-world sleep scenarios and improve it for continuous monitoring in clinical and home settings.

Keywords: Heart rate monitoring, Sleep studies, ECG-Trunk Muscle Signal, Discrete wavelet transform, Signal processing, Noise reduction.

1. INTRODUCTION

Heart rate (HR) serves as a fundamental indicator of cardiovascular function, and its continuous assessment during sleep offers critical insights into both cardiac and neurological health. Tracking HR while asleep contributes to the early detection of sleep-related disorders and improves our understanding of autonomic nervous system activity across various sleep phases, including rapid eye movement (REM) and non-rapid eye movement (NREM) stages [1], [2]. Notwithstanding the acknowledged significance of such monitoring, traditional instruments—such as electrocardiographic monitors and motion-based sensors—encounter enduring constraints. These systems frequently struggle to precisely differentiate between heart rate alterations resulting from intrinsic physiological responses and those caused by postural adjustments or muscular activity during sleep [3].

Electrocardiogram (ECG)-based heart rate monitors are the benchmark in sleep research since they can directly capture cardiac signals. Nonetheless, they are susceptible to interference, especially from muscular contractions, which generate distortions that can hide tiny heart rate variations.[4]. Accelerometers are often used in conjunction with ECGs to detect gross body movements and help contextualize HR trends. Nevertheless, accelerometers typically lack the sensitivity required to detect fine muscle activity that can still distort HR readings [5], [6].

Recent studies have concentrated on the amalgamation of ECG recordings with trunk muscle signal analysis to enhance the reliability of heart rate monitoring. The ECG-Trunk Muscle Signal (ECG-TMS) method tries to separate muscle noise from heart signals, which makes heart rate measurements more accurate. Advanced signal processing tools, such as wavelet decomposition, which breaks down ECG signals into different frequency bands, are at the heart of this method. Wavelet-based analysis offers a sophisticated method for extracting precise heart rate data by isolating pertinent cardiac components from high-frequency noise. [7], [8]. Along with these methodological

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improvements, wearable devices have also changed. For example, the Shimmer3 ECG platform can record several physiological signals at once. These devices allow for continuous real-time monitoring and the storage and offline analysis of large datasets. Recent advances have made heart rate monitoring better, but there are still big problems to solve, especially when it comes to reliably separating heart signals from noise caused by muscles while sleeping. Even with accelerometers, which are good at picking up big body movements, it's still not good enough to pick up on small muscle movements that can change heart rate readings. [9]. Another limitation is the dependence on small-scale studies or controlled environments that fail to represent the complexity of natural sleep. [11], [12].

Based on these flaws, this study suggests a new way to improve the accuracy and measurement of heart rate during sleep. The technique depends on using discrete wavelet decomposition to separate trunk muscle activity from ECG recordings. This makes it easier to tell the difference between physiological HR changes and changes caused by physical movements. The study seeks to assess the robustness and reliability of the ECG-Trunk Muscle Signal (ECG-TMS) framework by implementing this technique in controlled, sleep-like experimental conditions.

2. MATERIAL AND METHODS

2.1 Experimental Protocol

The experiment sought to evaluate the efficacy of the ECG-Trunk Muscle Signal (ECG-TMS) method for heart rate (HR) monitoring in sleep-like conditions. A healthy adult male volunteer, aged 34 years, weighing 90 kg and measuring 1.88 m, was recruited for the study. The participant exhibited no known cardiovascular or neurological disorders and refrained from caffeine consumption and physical exertion for a minimum of five hours preceding the session. We used a Shimmer3 ECG device to collect data (see [Figure 1]), with electrodes placed under the pectoral muscles to record signals from both the heart and trunk muscles. We took samples of ECG data at a rate of 500 Hz and saved them to an internal SD card for later offline analysis.

Figure 1. ECG Shimmer3 device

2.2 Electrode Placement

To ensure reliable detection of both cardiac activity and trunk muscle signals, ECG electrodes were strategically positioned on the torso, specifically beneath the pectoral muscles, as illustrated in [Figure 2].

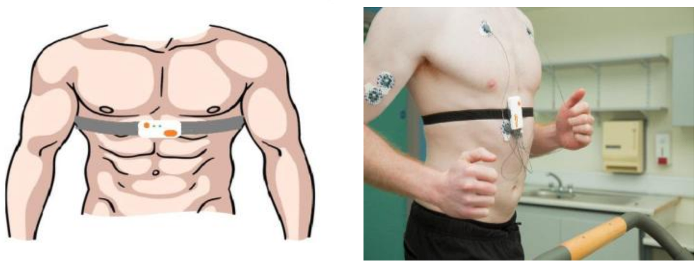

Figure 2. Electrode placement on the trunk muscles for ECG signal acquisition, as described [12]

2.3 Data Collection Configuration

The ECG signal was sampled at a rate of 500 Hz, providing adequate temporal resolution to capture both detailed cardiac activity and variations associated with muscle signals. Simultaneously, accelerometer data were collected to enable comparative analysis of body movements throughout the recording session.

2.4 Data Recording Protocol

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Data acquisition took place in a controlled environment designed to mimic sleep conditions. The recording protocol included four distinct phases:

Resting Period (Baseline): The subject remained completely still for five minutes to establish baseline physiological measurements.

Body Movement Period: A deliberate body shift was performed to simulate pronounced movement during sleep.

Second Resting Period: The participant resumed a stable position for an additional five minutes to assess the consistency and stability of the ECG-TMS method.

Light Body Movement Period: Subtle limb adjustments, such as slight arm or leg movements, were introduced to evaluate the method's sensitivity to minor muscular activity.

All physiological signals were stored locally on the device's SD card for subsequent offline processing using custom-developed signal analysis algorithms.

3. Results

3.1 ECG-TMS Signal Analysis: The analysis revealed distinct patterns of ECG-TMS activity across the four periods refer to [Figure 3].

Figure 3. Changing position of the subject

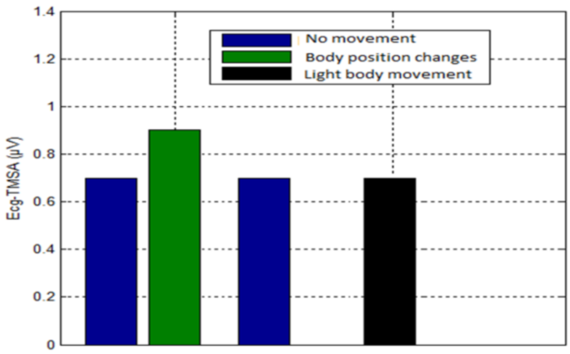

Figure 4. ECG-TMS signals during different experimental periods

Resting Periods (Periods 1 and 3): The ECG_{TMS} signal was minimal, indicating low muscle activity during these stable phases as shown in [Figure 3].

Body Movement Period (Period 2): A significant increase in ECG_{TMS} amplitude was observed, correlating with the subject's deliberate body movement, refer to [Figure 3].

Light Body Movement Period (Period 4): The ECG_{TMS} signal displayed moderate increases, representing the subtle muscle contractions associated with small limb adjustments.

These findings confirm that the ECG-TMS signal effectively captures trunk muscle activity, particularly during periods of movement, while remaining low during resting phases.

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3.2 Accelerometer Data

Accelerometer readings collected simultaneously with the ECG signal were analyzed to compare their sensitivity to movement detection, refer to [Figure 5]:

***Body Movement Period (Period 2)**:* The accelerometer showed significant changes in all three axes, consistent with the observed ECG_{TMS} activity.

***Light Movement Period (Period 4)**:* While the accelerometer detected only minimal changes, the ECG_{TMS} signal showed a noticeable increase, indicating the presence of subtle muscle contractions.

***Resting Periods (Periods 1 and 3)**:* Both the accelerometer and ECG_{TMS} showed low activity, confirming the absence of major movements.

The comparison highlights the ECG-TMS method's superior sensitivity to subtle movements that the accelerometer failed to capture.

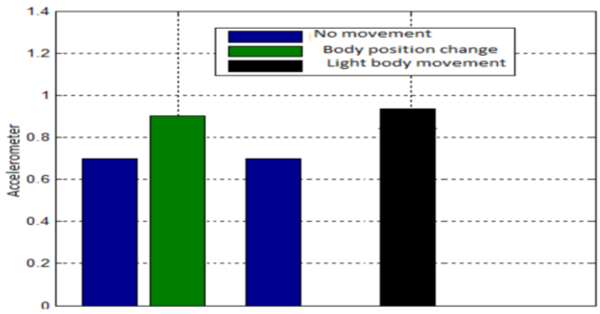

Figure 5. Accelerometer readings during different experimental periods

3.3 Heart Rate Variability

Heart rate (HR) was calculated from the reconstructed ECG_{heart} signal using the Pan-Tompkins algorithm. The results revealed clear distinctions between the different periods:

***Resting Periods (Periods 1 and 3)**:* HR remained relatively stable, with minor fluctuations reflecting physiological baseline variability.

***Body Movement Period (Period 2)**:* A significant increase in HR was observed, corresponding to the high level of ECG_{TMS} activity during deliberate movement.

***Light Movement Period (Period 4)**:* HR showed slight increases, demonstrating the method's ability to detect changes caused by minor muscle contractions.

[Figure 6] presents HR trends across all periods, showing a strong correlation between ECG_{TMS} activity and HR variations.

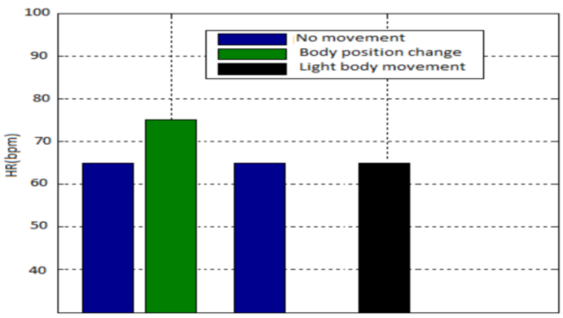

Figure 6. Heart rate variations during different experimental periods

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3.4 Comparison of Methods

To assess the efficacy of the ECG-TMS method, heart rate measurements and trunk muscle activity detection were juxtaposed with accelerometer data:
During ***Period 2***, both the ECG-TMS and the accelerometer picked up on a lot of activity, which was in line with the rise in heart rate.
Period 4: The ECG-TMS method could pick up on muscle activity that the accelerometer missed, which made heart rate analysis more accurate.
Both techniques confirmed that there was very little muscle activity during these resting periods ***(periods 1 and 3),*** which was in line with stable heart rate measurements.
Overall, these results show that the ECG-TMS method is better at picking up changes in muscle activity and heart rate than traditional accelerometer-based monitoring.

4. DISCUSSION

The results of this study validate the efficacy of the ECG-TMS method in differentiating trunk muscle activity from cardiac signals, thereby improving the precision of heart rate (HR) monitoring in simulated sleep conditions.

4.1 Comparison with Traditional Methods

The ECG-TMS method has a number of benefits over traditional HR measurement methods that use separate heart rate monitors or accelerometers, as shown in [Table 1]:

Table 1 Comparative Evaluation of ECG-TMS with Traditional HR Monitoring Methods

Criteria	**ECG-TMS Method**	**Traditional HR Monitors**	**Accelerometers**
Sensitivity to Movements	High sensitivity to subtle muscle contractions, even during light movements (e.g., Period 4).	Limited sensitivity; prone to noise from muscle artifacts.	Effective for detecting gross body movements but fails to capture subtle contractions.
Noise Reduction	Significantly reduces noise by isolating ECG_{TMS} from ECG_{heart}, leading to improved SNR.	Struggles with noise, particularly from muscle activity and external interference.	Does not handle noise in cardiac signals.
HR Measurement Accuracy	High accuracy due to clean cardiac signals after artifact removal.	Accurate during periods of low or no movement but less reliable during active phases.	Indirectly measures HR by inferring activity; less precise.
Integration with Devices	Compatible with wearable ECG systems like Shimmer3, offering real-time and offline analysis.	Widely used in clinical and wearable devices but lacks advanced artifact filtering.	Commonly integrated in wearable devices but limited to motion analysis.
Complexity of Processing	Requires advanced signal processing (DWT) for artifact separation, which increases computational demand.	Simple signal processing, suitable for real-time use but less robust.	Minimal processing needed, focusing on motion detection.
Applications	Ideal for sleep studies, cardiovascular monitoring, and wearable technologies requiring precise HR analysis.	Suitable for general HR monitoring and clinical applications without movement artifacts.	Useful for detecting body movements and activity levels rather than HR.

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6. CONCLUSION

This study proposed and evaluated a novel ECG-Trunk Muscle Signal (ECG-TMS) method for heart rate monitoring during sleep. Using discrete wavelet transform, the method isolates trunk muscle artifacts from ECG recordings, enhancing signal quality and HR measurement accuracy. Results under controlled sleep-like conditions demonstrate robust performance in detecting subtle muscle contractions often missed by conventional accelerometer-based systems. The improved signal-to-noise ratio and sensitivity to minor body movements confirm its suitability for analyzing HR dynamics across sleep phases. Compatibility with wearable devices like the Shimmer3 ECG unit supports real-time and offline monitoring applications. These findings highlight ECG-TMS potential for advancing sleep research, cardiovascular diagnostics, and personal health monitoring. Future work will optimize the algorithm for real-time implementation, validate effectiveness in natural sleep conditions, and extend the study to broader, more diverse populations, particularly individuals with sleep or cardiovascular disorders. The ECG-TMS method represents a promising step toward establishing a more accurate, noise-resilient, and versatile standard for HR monitoring in clinical and ambulatory environments.

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