SleepPal: A Sleep Monitoring System for Body Movement and Sleep Posture Detection

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Keywords: Sleep, Sleep Posture, Nocturnal Body Movements, Sleep Quality, Actigraphy.

Abstract: Sleep posture is a clinical relevant parameter for it is associated with several pathologies and affects the quality of sleep. In this paper, we propose SleepPal a sleep monitoring system for body movement and sleep posture detection. It consists of a wearable device that extracts data from a 3-axis accelerometer and transmits them to a remote monitoring station. A threshold-based algorithm is used to detect body movement and to distinguish between transitions. The proposed system will also evaluate the sleep quality index. Experiments were conducted on 10 subjects and results showed 88% of sensitivity and 82% of accuracy.

1 INTRODUCTION

Movements during sleep and body postures were reported to be associated with different pathologies (Horne et al., 2002) and decreased sleep quality (De Koninck et al., 1983). For example, patients with insomnia spend more time on their back (De Koninck et al., 1983), whereas patients with heart failure prefer to sleep on their side (Leung et al., 2003) (Hoffstein, 1996). Sleep apnea is also increased by certain sleep positions such as supine position (Cartwright, 1984). Obviously, the number of pathologies that implies sleep disorders has become of significance importance that it became prime to evaluate the quality of sleep. Accurate measurement of sleep quality is performed normally by overnight polysomnography (PSG) which includes several physiological measurements such as Electrocardiogram (ECG), Electroencephalogram (EEG), Electromyogram (EMG), respiration and body movement during sleep (Colman, 2006). PSG is a reliable method used in sleep diagnosis, but it is not without drawbacks. It involves high costs associated with the utilisation of complex equipment and require continuous monitoring from healthcare professionals. In addition, attaching many electrodes to the patient's body is considered intrusive, which can disturb sleep. Thus, the measured data may not accurately represent the sleep behavior of the patients. These drawbacks make PSG impractical to be implemented within a long-term sleep monitoring system within homes. Alternately, actigraphy has been recently adopted for continuous measurement of sleep activity. The device is called an actigraph. It is composed of motion sensors such as accelerometers. It is capable of measuring and logging the movement. The advantages of actigraphy over PSG are many, to note the cost, the low number of sensors, the minimum intrusiveness and and the continuous log over long periods of time (i.e Weeks, Months).

In this paper, a complete monitoring system including a wearable device for a long-term sleep monitoring is proposed. The wearable device named SleepPal is comfortable to wear with low intrusiveness for the patient and its deployment does not require any intervention from a trained expert. It extracts data from a 3-axis accelerometer and transmits them to a remote monitoring station over a wireless network connection. The body posture, the position, and the movements can be determined based on multiple features extracted from the acceleration data. A simple but accurate threshold-based algorithm is developed that detects the transitions between different body postures that are defined in a state diagram. Finally, the sleep quality indicator will be determined

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Ibrahim, A., Chaccour, K., El Hassani, A. and Andres, E.
SleepPal: A Sleep Monitoring System for Body Movement and Sleep Posture Detection.
DOI: 10.5220/0011840900003476
In *Proceedings of the 9th International Conference on Information and Communication Technologies for Ageing Well and e-Health (ICT4AWE 2023)*, pages 40-47
ISBN: 978-989-758-645-3; ISSN: 2184-4984

considering the number of transitions between two sleep postures over the period of the sleep.

The rest of this paper is divided as follows. Section 2 surveys existing solutions related to bed movements detection. Section 3 elaborates on the material and methods followed in the development and implementation of the sleep monitoring system. Section 4 explains the experimental evaluation of the proposed system and discusses the obtained results. Finally, Section 5 presents the concluding remarks and the future directions of this research.

2 RELATED WORK

Actigraphy has been used in various areas of medical research, typically for monitoring motion-related sleep disorders. In fact, It has been used in many studies since 30 years ago. (Kupfer et al., 1972) reported a correlation between EEG signals, wrist activity, and wakefulness in 1972. (Sadeh et al., 1995) concluded that normal subjects showed more than 90% correlation when comparing actigraphy data with PSG. By 1995, sufficient experimentation had been carried out to finally enable the Standards of Practice Committee of the American Sleep Disorders Association (ASDA) to support the use of actigraphy in evaluating certain aspects of sleep disorders, such as insomnia, circadian sleep–wake disturbances, and periodic limb movements. On an higher level, a generic classification of bed related systems was proposed by (Ibrahim et al., 2021). The authors classified these systems into Wearable Systems (WS), Non-Wearable Systems (NWS), and Fusion Systems (FS).

- **Wearable Systems (WS)**: Many studies have been reported to use actigraphy in WS. For instance, (Miwa et al., 2007) proposed a rollover detection system using a SenseWear Pro2 Armband. They used the maximum and the mean acceleration in the x and y directions to identify the posture differences using a threshold based algorithm. The experiments showed that 82.4% of rollovers were detected. Similarly, (Acharya, 2020) proposed a rollover detection system using the ADXL335 accelerometer attached on socks where acceleration row data was used in a threshold based algorithm.
- **Non-Wearable Systems (NWS)**: Other studies reported the use of unobtrusive sensors used for bed movement detection. These include load sensors installed under bedposts. (Adami et al., 2008) proposed a system for classification of movement in bed using load cells. The experiments were done on 15 participants and showed an accuracy of 84.6%. (Beattie et al., 2011) also used load cells under bedposts giving a total of 4 cells. The classification of the sleeping posture was done using K-Means classifier of the bed's Center of Pressure (CoP) in the x and y directions. The experiments showed an accuracy of 68%, 57%, 69%, and 33% for the back, right, left, and stomach postures respectively. The problem with this approach is that CoPy values for back and stomach postures are the same so the classifier fails to distinguish between them. An unrestrained sleep monitoring system using cameras has been also proposed to monitor sleep postures. (Lee et al., 2015) proposed a system to monitor the sleeping position using a Kinect sensor. They used Kinect's skeleton and Kinect's infrared camera to detect the body joints. The joint model given by the Kinect has 25 points. The authors recorded the x, y and z positions of those points and calculated the sleep movement taking the Euclidean distance between those points with respect to time. However, the procedure may still be considered as an invasion of privacy for some patients which makes its utilisation not suitable.
- **Fusion Systems (FS)**: Fusion of sensors will form a multi-channel source of data which can provide more accurate analysis. For instance, (Nam et al., 2016a) used a pressure sensor and an accelerometer to extract data on motion, respiration, body activity, and heart rate. These data were used to measure sleep quality by estimating the depth of sleep, the number of apneaic episodes and the periodicity. The experimental results demonstrated that the proposed system is effective in measuring the physiological factors of sleep quality.

In addition to proposing a low cost device used to identify body posture and transitions, this paper seeks to contribute in proposing a body transition matrix that could be used in any threshold based algorithm.

3 MATERIALS AND METHODS

3.1 Wearable Sensor

Continuous sleep monitoring must be unobtrusive and have minimal physical impacts on bed activities. For these reasons, we proposed our sleep monitoring system SleepPal. SleepPal includes a small device that could be attached to the center of the chest and measures the body acceleration in the three axes. The device transmits real-time accelerometer raw data over the Wi-Fi network to a monitoring and visualization software installed on a remote computer. The architecture of SleepPal is illustrated in Figure 1. The system is composed of an Inertial Measurement Unit (IMU) and a Microcontroller Unit (MCU). To ensure the wireless communication, ESP8266 NodeMCU is used with IMU MPU6050 which includes the ADXL345 triaxial accelerometer.

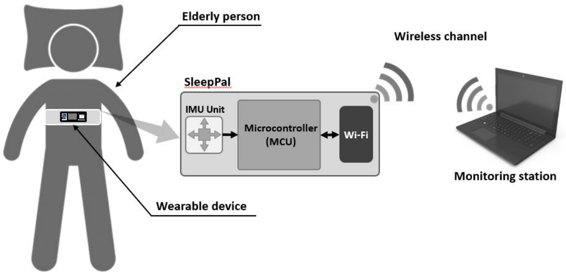

Figure 1: Architecture of SleepPal.

3.2 Sleep Postures and Bed Movements

The objective of SleepPal is to detect and record the sleep posture and bed movements in order to build a sleep monitoring database. The device will be able to detect and store each posture and each movement in the database for further analysis and evaluate the sleep quality. Generally, sleep postures on the bed could be classified into four categories namely, the front, the back, the left, and the right (Nam et al., 2016b). The same terminology is also adopted by (Hoque et al., 2010). This terminology will be adopted for the rest of this paper. These postures are as follows:

- Supine Posture (SP): The subject is lying on his back (back posture);
- Prone Posture (PP): The subject is lying on his stomach (front posture);
- Right Lateral Posture (RLP): The subject is lying on his right side (right posture);
- Left Lateral Posture (LLP): The subject is lying on his left side (left posture);

The sleeping posture is identified based on the body movement detected and the raw data extracted from the accelerometer. By knowing which movement was performed, we can derive the position relatively to the edges of the bed. The motion data is used to validate the last performed posture.

A change in the sleeping posture also called rollover is defined as a series of trunk movements beginning from the current static posture to the next static posture through rotational motions during sleep (Miwa et al., 2007) (Acharya, 2020). Therefore, the most adequate location to fix our device is on the chest. Referring to this definition, each static posture is defined as a state and each rollover is defined as a transition. SleepPal will count the rollovers to determine the position and evaluate the sleep quality. We identify four states and eight possible transitions as illustrated in Figure 3.

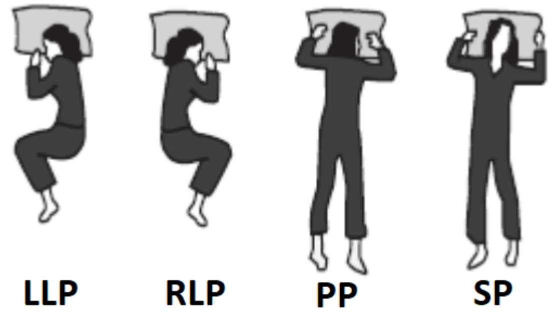

Figure 2: Common sleeping postures. From left to right: Left Lateral Posture (LLP), Right Lateral Posture (RLP), Prone Posture (PP) and Supine Posture (SP).

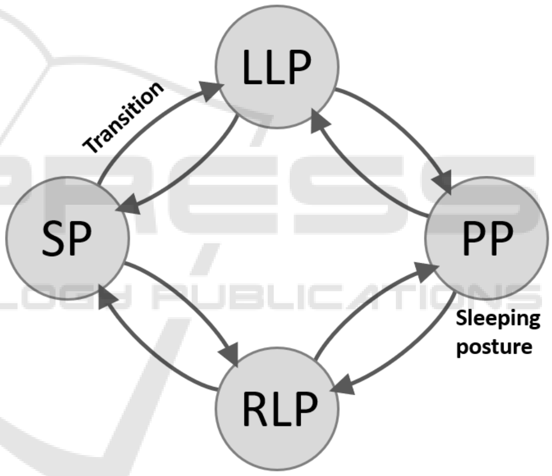

Figure 3: Sleep postures and movement transition scheme.

On the side note, there can be other transitions such that from RLP to LLP and vice versa or from PP to SP and vice versa, however, such transitions are a composition of two consecutive transitions.

3.3 Features Extraction

The data from the accelerometer is collected in raw mode, which provides the acceleration data in actual g-forces. The sampled data are stored and analysed in epoch of an approximate length of 2s. The extracted features are the Mean Acceleration ($\bar{A}_{(T)}$, $\bar{A}_{(L)}$), and the Mean of Absolute Difference ($\overline{MAD}_{(T)}$, $\overline{MAD}_{(L)}$) for both the transverse and longitudinal directions as well as the Posture Difference (ΔP) proposed by (Miwa et al., 2007). Herein, $MAD_{(d)}$ is used as an indicator of the movement intensity, the Mean Acceleration $\bar{A}_{(d)}$ is used to identify the direction, and (ΔP) is used to identify the difference in postures. These features are formulated below:

3.3.1 Mean of Acceleration ($\bar{a}$)

It represents the average of acceleration in both transverse and longitudinal directions (d) defined in g and shown in Equation (1).

$$\bar{A}_{(d)} = \frac{1}{n}\sum_{i=1}^{n} a_i \tag{1}$$

Where n is the number of samples in the epoch and a_i is the acceleration sample.

3.3.2 Mean of Absolute Difference (MAD)

It describes the mean distance of data points about the mean in both transverse and longitudinal directions (d) defined in g and shown in Equation (2).

$$MAD_{(d)} = \frac{1}{n}\sum_{i=1}^{n} |r_i - \bar{r}| \tag{2}$$

Where n is the number of samples in the epoch, r_i is the i_{th} resultant sample within the epoch and $\bar{r}$ is the mean resultant value of the epoch.

3.3.3 Posture Difference (ΔP)

It represents the difference in average acceleration $\bar{A}_{(T)}$ and $\bar{A}_{(L)}$ defined in g^2 as shown in Equation (3). We designated ΔP as Posture Difference between time t and $t-1$.

$$\Delta P_t = (\bar{A}_{(T)_t} - \bar{A}_{(T)_{t-1}})^2 + (\bar{A}_{(L)_t} - \bar{A}_{(L)_{t-1}})^2 \tag{3}$$

Where $\bar{A}_{(T)}$ is the average acceleration in the transverse direction, and $\bar{A}_{(L)}$ is the average acceleration in the longitudinal direction.

3.4 Detection Algorithm

According to the position of the accelerometer installed in the wearable device illustrated in Figure 4, the y-axis will represent the transverse direction and the z-axis will represent the longitudinal direction. When stationary, the acceleration over the z-axis is equal to the gravitational force ($+1g$), and it should be ($0g$) on the y-axis. Thus, the value of the z-axis should be positive in SP, and negative in PP. On the other hand, the value of the y-axis should be positive when moving right and negative when moving left. Ideally, when moving to the LLP, the acceleration over the y-axis should be equal to ($-1g$) and ($0g$) in the z-axis. Alternately, when moving to the RLP, the acceleration over the z-axis should be equal to ($+1g$) and ($0g$) in the y-axis.

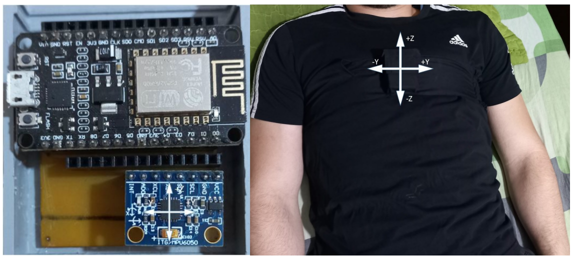

Figure 4: Positioning of SleepPal wearable device.

The signal of ΔP and $MAD_{(d)}$ in both directions during a transition or a rollover corresponds to an increase in both values since $MAD_{(d)}$ is influenced by the movement intensity and ΔP expresses the difference in posture between time t and $t-1$. Signals of the above features were exploited experimentally in order to define and derive the below threshold values:

- Upper Posture value ($U_{\Delta P}$): corresponds to the lowest upper peak value of ΔP recorded.
- Upper $MAD_{(T)}$ Transversal value ($U_{MAD_{(T)}}$): corresponds to the lowest upper peak value of $MAD_{(T)}$ recorded.
- Upper $MAD_{(L)}$ Longitudinal value ($U_{MAD_{(L)}}$): corresponds to the lowest upper peak value of $MAD_{(L)}$ recorded.

The perfect lateral position is hard to achieve therefore we defined two additional thresholds:

- Upper $\bar{A}_{(L)}$ in both lateral postures ($U_{\bar{A}_{(L)}}$): corresponds to the highest value of $\bar{A}_{(L)}$ in the lateral position.
- Lowest $\bar{A}_{(L)}$ in both lateral postures ($L_{\bar{A}_{(L)}}$): corresponds to the Lowest value of $\bar{A}_{(L)}$ in the lateral posture.

Thus, a transition is detected when ΔP, $MAD_{(T)}$ and $MAD_{(L)}$ are higher than the defined thresholds as described in Equation (4):

$$\begin{cases} \Delta P_t > U_{\Delta P} \\ MAD_{(T)} > U_{MAD_{(T)}} \\ MAD_{(L)} > U_{MAD_{(L)}} \end{cases} \tag{4}$$

To classify the transition upon detecting a movement, we used $\bar{A}_{(T)_t}$, $\bar{A}_{(L)_t}$, and $\bar{A}_{(L)_{t-1}}$. The pattern in each transition is described in Table 1.

The proposed algorithm will use the peaks of the posture difference ΔP, $MAD_{(T)}$, and $MAD_{(L)}$ to detect body transitions and rollovers. Upon detecting a

Table 1: Body transition matrix.

↱	**SP**	**PP**	**LLP**	**RLP**
SP	NA	NA	$\bar{A}_{(L)_t} \searrow$ $\bar{A}_{(T)_t} \searrow$ $\bar{A}_{(L)_{t-1}} > U_{\bar{A}_{(L)}}$	$\bar{A}_{(L)_t} \searrow$ $\bar{A}_{(T)_t} \nearrow$ $\bar{A}_{(L)_{t-1}} > U_{\bar{A}_{(L)}}$
PP	NA	NA	$\bar{A}_{(L)_t} \nearrow$ $\bar{A}_{(T)_t} \searrow$ $\bar{A}_{(L)_{t-1}} < L_{\bar{A}_{(L)}}$	$\bar{A}_{(L)_t} \nearrow$ $\bar{A}_{(T)_t} \nearrow$ $\bar{A}_{(L)_{t-1}} < L_{\bar{A}_{(L)}}$
LLP	$\bar{A}_{(L)_t} \nearrow$ $\bar{A}_{(T)_t} \nearrow$ $L_{\bar{A}_{(L)}} < \bar{A}_{(L)_{t-1}} < U_{\bar{A}_{(L)}}$	$\bar{A}_{(L)_t} \searrow$ $\bar{A}_{(T)_t} \nearrow$ $L_{\bar{A}_{(L)}} < \bar{A}_{(L)_{t-1}} < U_{\bar{A}_{(L)}}$	NA	NA
RLP	$\bar{A}_{(L)_t} \nearrow$ $\bar{A}_{(T)_t} \searrow$ $L_{\bar{A}_{(L)}} < \bar{A}_{(L)_{t-1}} < U_{\bar{A}_{(L)}}$	$\bar{A}_{(L)_t} \searrow$ $\bar{A}_{(T)_t} \searrow$ $L_{\bar{A}_{(L)}} < \bar{A}_{(L)_{t-1}} < U_{\bar{A}_{(L)}}$	NA	NA

body movement, the algorithm will compute the difference in signals for $\bar{A}_{(T)}$ and $\bar{A}_{(L)}$ in order to determine the signal behavior. Finally, the algorithm will compare the signal patterns with the matrix of pattern behaviors presented in Table 1 in order to identify the transition type and the current sleep posture.

4 EXPERIMENTAL EVALUATION

The system was evaluated on data collected in laboratory. Experiments were conducted on 10 volunteering subjects aging between 18 and 40 and weighting from 52 to 106kg. The device was attached to the center of the chest. The volunteers didn't report any discomfort in wearing the device. Each subject simulated all sleep movements five times. Thus, each subject performed 40 transitions and each posture transition is performed 50 times. In order to confirm the volunteer's posture, we installed a video camera above the bed and recorded the body movements.

Figures 5, 6, 7, and 8 show the signals recorded during body movements transitioning contrariwise from SP to LLP, from SP to RLP, from PP to LLP, and from PP to RLP respectively. As shown, during any body movement, a peak of ΔP, $MAD_{(T)}$, and $MAD_{(L)}$ are recorded simultaneously. The signals of $\bar{A}_{(T)}$ and $\bar{A}_{(L)}$ differ according to the transition.

The signals of the $\bar{A}_{(L)_t}$ and $\bar{A}_{(T)_t}$ directions correspond to a decrease in both values during SP to LLP and RLP to PP transitions. This decrease is due to rotational motion to the left. In order to distinguish between these transitions, we used the $\bar{A}_{(L)_{t-1}}$ to identify the previous posture. Similarly, from the SP to LLP transition, the $\bar{A}_{(L)_{t-1}}$ value should be $(+1g)$ which is greater than $U_{\bar{A}_{(L)}}$ recorded in lateral postures, whereas in the RLP to PP transition, the $\bar{A}_{(L)_{t-1}}$ should be between $L_{\bar{A}_{(L)}}$ and $U_{\bar{A}_{(L)}}$. Contrarily, the signals observed in LLP to SP and PP to RLP correspond to an increase in both values but in the first transition, the $\bar{A}_{(L)_{t-1}}$ should be between $L_{\bar{A}_{(L)}}$ and $U_{\bar{A}_{(L)}}$ and in the second transition it should be less than $L_{\bar{A}_{(L)}}$. An increase in $\bar{A}_{(L)_t}$ along with a decrease in $\bar{A}_{(T)_t}$ are observed in RLP to SP and PP to LLP transitions. $\bar{A}_{(L)_{t-1}}$ should be between $L_{\bar{A}_{(L)}}$ and $U_{\bar{A}_{(L)}}$ in the first transition and less than $L_{\bar{A}_{(L)}}$ in the second. Finally, a decrease in $\bar{A}_{(L)_t}$ with an increase in $\bar{A}_{(T)_t}$ are observed in SP to RLP and LLP to PP transitions. $\bar{A}_{(L)_{t-1}}$ should be greater than $U_{\bar{A}_{(L)}}$ in the first transition and between $L_{\bar{A}_{(L)}}$ and $U_{\bar{A}_{(L)}}$ in the second.

Table 2 shows the detection results of the proposed algorithm. Since we considered any body movement is a rollover, the total number of rollovers is 400. The proposed algorithm detected a 352 rollovers confirmed to be correct. Consequently, 48 rollovers were undetected (false negative) and a total of 30 false positive detections were recorded. The efficacy and robustness of our algorithm are evaluated by measuring both the sensitivity (i.e. Detected rollovers over the total of number of rollovers) and the accuracy (i.e. Ability of the system to detect the rollovers) which are recorded to be equal to 88% and 82% respectively.

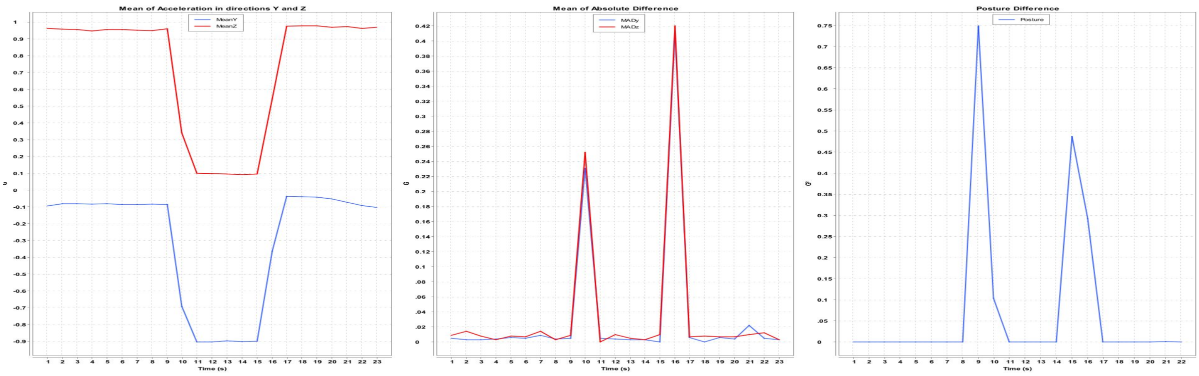

Figure 5: Signals during movement from SP to LLP and vice versa.

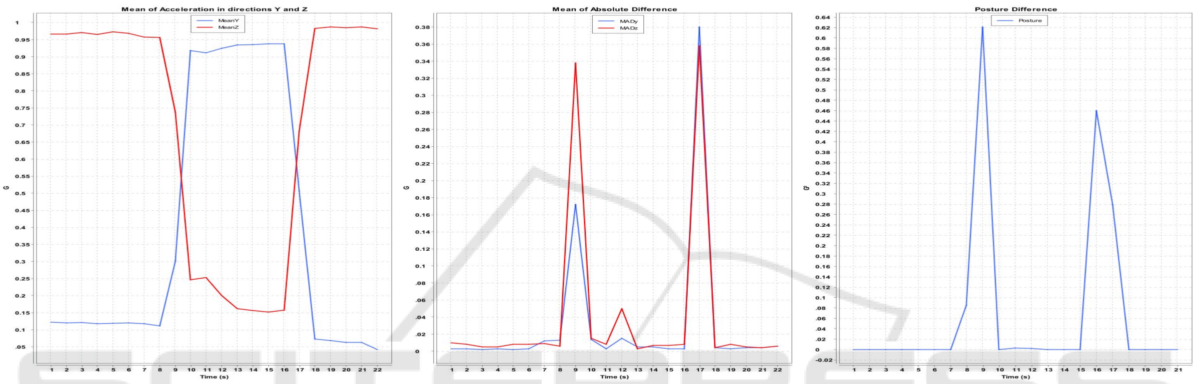

Figure 6: Signals during movement from SP to RLP and vice versa.

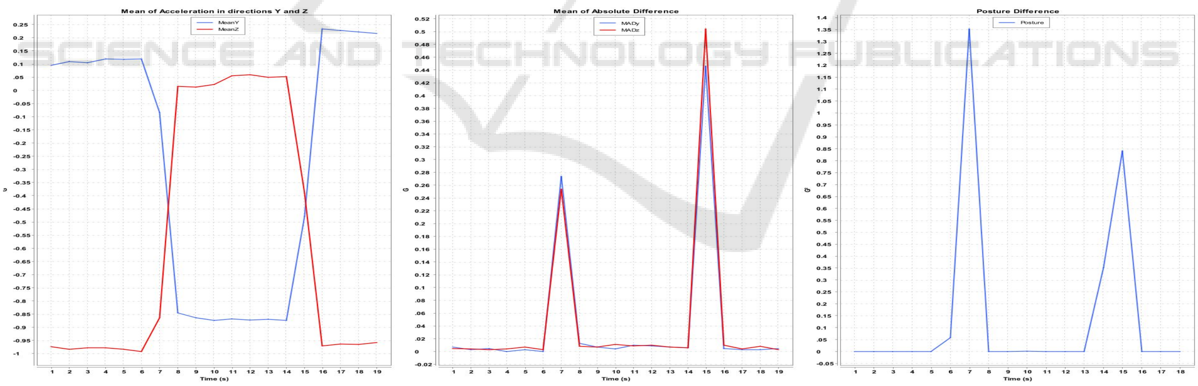

Figure 7: Signals during movement from PP to LLP and vice versa.

5 SLEEP QUALITY EVALUATION

Human sleep can be classified into Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM). The latter is further divided into three stages, N1-N3. Each stage of sleep includes variations in the brain wave pattern and eye movements. The body cycles through all of these stages approximately 4 to 6 times each night, averaging 90 minutes for each cycle (Memar and Faradji, 2017). REM and N1 stages are the lightest sleep, while N3 stage is the deepest sleep. In general, body movements increase during light sleep and decrease during deep sleep. Thus, the sleep can be classified into two stages, deep sleep and light sleep based on the frequency of body transitions detected. Hence, and upon detecting a body transition, SleepPal will record the time and will compare it to the time of the previously recorded body transition. Consequently, the interval between body transitions is computed and compared to a threshold

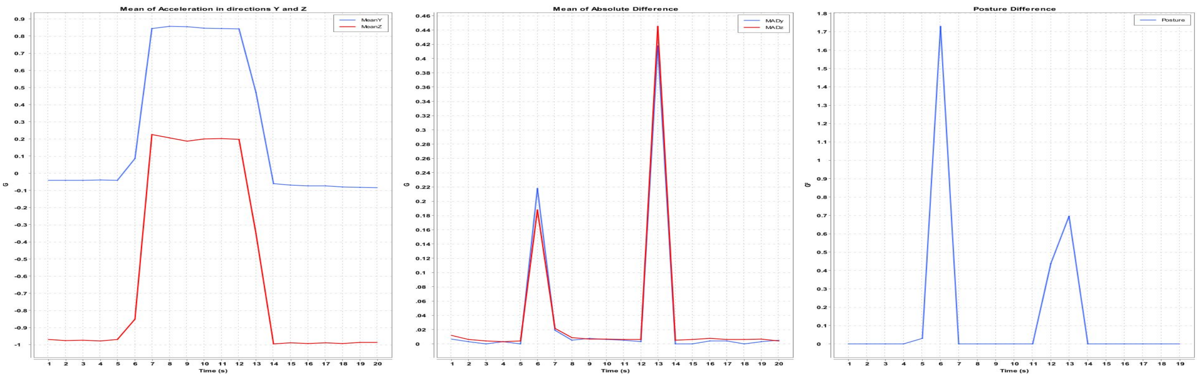

Figure 8: Signals during movement from PP to RLP and vice versa.

Table 2: Results of the detection algorithm.

#	Posture Transitions	Detection
1	SP → LLP	46/50
2	SP → RLP	47/50
3	LLP → SP	45/50
4	RLP → SP	45/50
5	PP → LLP	43/50
6	PP → RLP	43/50
7	LLP → PP	42/50
8	RLP → PP	41/50

as shown in Equation (5).

$$\begin{cases} DeepSleep = BM_t - BM_{t-1} \geq time_{th} \\ LightSleep = BM_t - BM_{t-1} < time_{th} \end{cases} \tag{5}$$

Where BM_t and BM_{t-1} are the body movements at times t and $t-1$ respectively. $time_{th}$ is the time threshold equal to 20 minutes according to (Miwa et al., 2007).

The time of each sleep stage will be recorded in order to evaluate the sleep quality. The latter is depending on several factors such as genetics, sleep habits, medical problems, and essentially sleep depth which is considered the most important in evaluating sleep quality. Thus, we determined the sleep quality in term of the sleep depth according to Equation (6) as follows:

$$QI_{SleepQuality} = \frac{d_{DeepSleep}}{d_{Total}} \tag{6}$$

Where $QI_{SleepQuality}$ is the sleep Quality Index, $d_{DeepSleep}$ is the duration of the deep sleep stage, and d_{Total} is the total sleep duration.

6 CONCLUSION

In this paper, we developed a body movement and body posture classifier using an accelerometer device attached to the center of the chest. The proposed system is based on a simple threshold algorithm and uses multiple features extracted from the raw acceleration data. The efficacy and robustness of our algorithm are evaluated by measuring both the sensitivity and the accuracy which were recorded to be equal to 88% and 82% respectively. In order to evaluate the sleep quality, we distinguished between deep sleep and light sleep using a simple threshold-based equation. Our proposed sleep monitoring system can be used for monitoring sleep quality in hospitals by interfacing it with the existing nurse call system.

Further research will exploit the limitations of the device in settings where sliding in bed remains undetected and motion noise caused by the fixation of the sensor must be removed. We will also emphasize the relationship between sleep quality, sleep disorders and nocturnal falls.

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