Periodic Leg Movement (PLM) Monitoring using a Distributed Body Sensor Network

Priyanka Madhushri, Beena Ahmed, Thomas Penzel, Emil Jovanov

***Abstract*— Wireless sensors networks represent the architecture of choice for distributed monitoring due to the ease of deployment and configuration. We developed a distributed sleep monitoring system which combines wireless inertial sensors SP-10C by Sensoplex controlled by a custom smartphone application as an extension of the polysomnographic (PSG) monitor SOMNOscreen plus from Somnomedics. While existing activity monitors are wired to the SOMNOscreen, our system allows the use of wireless inertial sensors to improve user's comfort during sleep. The system is intended for monitoring of periodic leg movements (PLM) and user's activity during sleep. Wireless sensors are placed on ankle and toes of the foot in a customized sock. An Android app communicates with wireless sensors over Bluetooth Smart (BTS) link and streams 3D accelerometer values, 4D unit quaternion values and timestamps. In this paper we present a novel method of synchronization of data streams from PSG and inertial sensors, and original method of detection of PLM events. The system was tested using five experiments of simulated PLM, and achieved 96.51% of PLM detection accuracy.**

I. Introduction

Sleep disorders such as insomnia adversely affect people's sleep and finally the overall quality of life. Causes of secondary insomnia include anxiety, depression, stress, excessive caffeine or alcohol and poor sleep schedules. Primary insomnia has no recognized other reason. Studies show that more than 40 million Americans suffer from some form of chronic sleep disorder [1]. Insomniacs have problems falling asleep, maintaining good sleep or excessive sleepiness in the daytime. Insomnia can be a primary sleep disorder characterized by disturbances in the duration, quality and/or the timing of sleep [2]. In the new era of sleep monitoring, wearable sensors, advanced sensing and wireless technology can be used to significantly improve the diagnosis of insomnia in a systematic manner with a well established framework.

In recent years, several sleep monitoring systems have been developed [2], that are highly automated, and portable for use at home. However the entire setup integrates a number of devices, sensors, and wires that has been proven to significantly disturb sleep of users, particularly during the first night of monitoring [3]. Moreover, wired sensors and electrodes are also inconvenient and uncomfortable, which may affect the subject's health and mood [4]. Hence introducing wireless sensor technology in insomnia monitoring would be a great advancement in this field. The wireless sensors network (WSN) or body sensor network (BSN) represent an architecture of choice for distributed monitoring due to the ease of deployment and configuration [5]. It is the most emerging and fast growing research area. Due to its broad range of applications in the distributed health monitoring systems, it has drawn great attention of researchers in recent years.

The assessment of insomnia requires the exclusion of other sleep disorders and as such involves the detection of Periodic Leg Movements (PLM), a sleep disorder where patients produce repetitive movements of the lower limb, including movements in the toe, ankle and entire lower leg [6]. PLMs create significant disturbances during sleep and can also lead to arousals and hence insomnia [7]. According to the current World Association of Sleep Medicine (WASM) standard, the Electromayographic (EMG) activation of the anterior tibialis muscle can characterize PLM events [8]. The International Classification of Sleep Disorder (ICSD) counts a leg movement of duration 0.5-5 seconds as a PLM. It generally occurs in the series of four or more movements during any sleep stage (wake excluded) at intervals of 5-90 seconds [9]. When occurring periodically, they are called PLM. The PLM index is defined as the number of PLM events per hour of the total sleep time is the measure of frequency of PLM [10]. Currently PLMs are detected using EMG of one or two legs with standard electrodes.

The main problem in PLM monitoring using EMG electrodes with a PSG system is the inconvenience the wired system causes. Accurate detection of PLM events requires placement of the EMG electrodes 5 cm apart on the middle of the tibialis muscle, which requires long wires from legs to the monitor usually worn on the chest. In some recent work accelerometers have been used to quantify PLMs [11]. Bhagat et al. used an accelerometry based mobile health device to monitor activities during sleep [12]. Terril et al. used tri-axial accelerometry system for the detection of PLM and made a comparison analysis with results from the EMG signal [6]. The main issue of accelerometer based systems is reliable detection of leg movements that satisfy the PLM standard from the random body motion in all the different positions during sleep.

We developed a body sensor network of inertial sensors synchronized with a commercial PSG system for sleep monitoring to detect and quantify PLMs and improve comfort levels while the patient is asleep. In this paper we

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present the system organization and the results of the analysis of the whole night monitoring, which include an analysis of the wireless channel reliability and synchronization of the sensor streams.

II. METHODS

A. System Architecture

The proposed system architecture of our sleep monitoring system is presented in Fig. 1. The system consists of a PSG system, two inertial sensor modules (SP-10C), and a smartphone. The PSG system has several standard sleep study sensors wired with a central device called Somnoscreen (SSC). This PSG system records data overnight stores in a flashcard or transmits wirelessly to a workstation. The EMG signal and other signals are recorded using a PSG monitor.

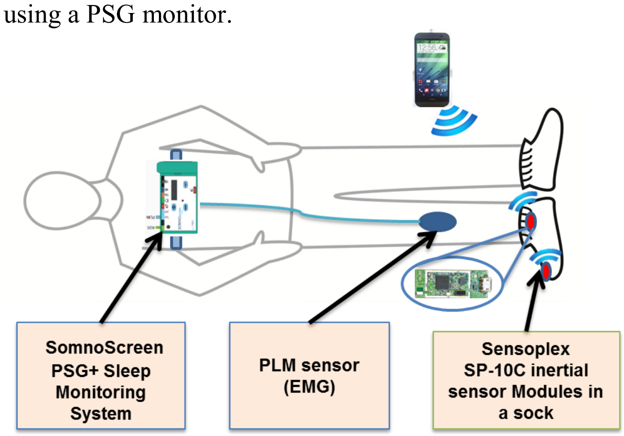

Figure 1. System architecture of the proposed solution

The two SP-10C inertial sensors are placed on the ankle and toe of a fitted sock to keep them stationary relative to the patient during the overnight recording as presented in Fig. 2. The Sensoplex SP-10C inertial sensors are compact and low power smart sensor modules that combine a 3-axis gyroscope, 3-axis accelerometer, and 3-axis magnetometer with BTS. Sensors use 120 mAh Li-ion-polymer batteries, which can last up to 11-12 hours making them suitable for sleep studies [13].

Our custom Smartphone application supports multiple SP-10C sensors communicating simultaneously via BTS. As the sensors act as a Generic Attribute Profile (GATT) server, we configured our Android app to act as a GATT client. The GATT profile is a general specification for sending and receiving data over a BTS link [14]. All current low energy application profiles are based on GATT, which is available on Android starting from version 4.3 (API Level 18) [15].

B. Synchronization of Sensors

Distributed wireless sensor systems have to compensate for the drift of local on chip oscillators and error sources during intermittent communication which creates serious obstacles for time synchronization, particularly for long term monitoring [16]. Clock drift can occur in distributed systems due to environmental changes, such as pressure, temperature, and battery voltage [17]. The requirement to configure Smartphone application as a GATT client instead of a server complicates synchronization between the inertial sensors; the lack of a global clock resulted in unsynchronized data streams from individual sensors [18].

Since our PSG system uses autonomous operation with data records stored in local flash memory, we synchronize the inertial sensors externally by utilizing an auxiliary (AUX) input of the PSG system. We use a custom interface with optical isolation and generate a burst of 5 audio pulses every minute on Smartphone, at the beginning of each sleep study. These audio pulses are recorded in the PSG as analog auxiliary signals and used as time markers for precise time synchronization. Accurate time synchronization of both inertial sensors is crucial for accurate PLM detection with our algorithm. To achieve this, our custom app saves the timestamp values from both sensors and the smartphone every minute.

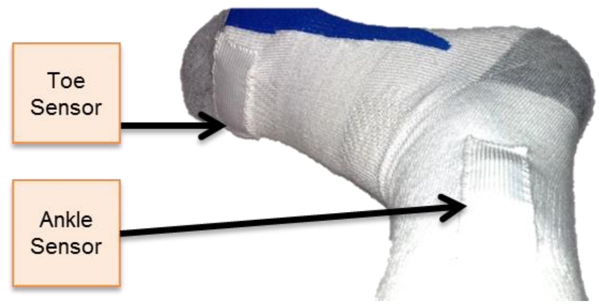

Figure 2. Placement of two wireless inertial sensors in the sock

Individual data streams are aligned using Dynamic Time Warping (DTW). DTW is a well known technique of optimal time alignment between signals where sequences are warped in non-linear fashion to match with each other [19]. In our preliminary experiments, the time difference between the Smartphone and PSG was in the range of 1 to 1.5 seconds for 8-9 hours of recording. However, the drifting in the inertial sensor clock with respect to the Smartphone was significantly more hence DTW was applied to overcome this drifting and synchronize all three independent data streams. The inertial sensor data was fully synchronized with the PSG data after the application of DTW algorithm.

C. PLM detection

We recorded 3D accelerometer data for translational movement and unit quaternion for rotational movement, along with timestamps from inertial sensors. As BTS is not designed for high frequency data streaming applications, we tested our Android application with different sampling rates to find the reliable operating sampling frequency.

To identify the PLMs, we calculated the 3D vector magnitude of the accelerometer, which was then filtered using an 8-pole Butterworth high pass filter with cutoff frequency 0.05Hz to remove the DC offset and then again filtered with moving average filter to quantify movements. As PLMs result in a large rotation of toe sensor value with a small rotation in the ankle sensor value [6], real PLM events can be discerned from the other regular random events. To distinguish between regular motion (Fig. 3a and 3b) and PLMs (Fig. 4a and 4b), we calculated maximum displacement, maximum velocity, maximum absolute rotation angle using quaternion values [20] and duration of movement for both toe and ankle. By applying binary classification using the support vector machine (SVM) technique, we trained our model with mean and standard deviation values of all calculated parameters to identify PLMs from the gross body motion. Our PLM detection algorithm detects only those movements as real PLM which satisfy the time duration and recurring interval criteria as per the PLM standard.

D. Experimental Validation

We designed a custom experiment to simulate PLM movements; experiments with five subjects were performed using this protocol. In each experiment, the subject completed a series of simulated PLM-like movements for different body positions and other sleep related events. First, the subject laid down on the back with the legs straight and created 6 PLM- like movements keeping approximately 5 seconds between each. The subject then turned right with the legs straight and after a minute repeated the 6 PLM-like movements. Finally the subject turned left with the legs kept straight and again repeated the PLM movements. Subjects were asked to perform several random movements during the experiment such as bending the knees and legs. The data collected was then used to test our time synchronization and PLM signal processing algorithm. The PLM detection algorithm was also tested for real patient data from whole night (8 hours 20 minutes) monitoring using complete system. Real PLM events were captured using PSG system based on the value of EMG signal.

III. Results

A. Time Synchronization

The time difference between the individual sensor and Smartphone was almost linear and compensated by using dynamic time warping. Analysis of the five overnight recordings indicate that the relative time difference between the sensors during one minute synchronization period is in the range of 200–400ms; after DTW processing, the time difference between individual samples was reduced to 5.12±2.99 ms.

BTS communication was not reliable at higher frequencies. We tested the accuracy rates for sampling frequencies from 10Hz to 100Hz. Table 1 shows the different accuracy rates for different sampling frequencies in terms of bit error rate. The best accuracy is obtained with a sampling frequency of 50Hz which uninterruptedly supports long term (overnight) streaming over BTS without any problems.

TABLE I. Results of reliability analysis over BTS

Frequencies→	<40Hz	**50Hz**	60Hz	70Hz	80Hz	90Hz	100Hz
S#1 bit error [%]	0	**0.019**	0.35	1.78	1.03	1.60	3.46
S#2 bit error [%]	0	**0.042**	0.47	1.36	2.58	1.85	6.47

B. PLM Detection

Table 2 presents the result of PLM detection algorithm using accelerometer and quaternion values from both the toe and ankle sensors. The sensitivity and specificity of the current version of our algorithm are 98.03% and 95.68% respectively. The accuracy of detection is 96.51%. For the real patient data, out of 149 PLM events marked by PSG, our algorithm was able to detect 136 of those events as true positive. Hence accuracy of detection for real time monitoring was 91.27%.

TABLE II. PLM Detection Results

Case num	Number of PLM events	Number of random events	True positive (TP)	True negative (TN)	False positive (FP)	False negative (FN)
1	39	57	38	54	3	1
2	33	59	33	58	1	0
3	26	52	26	49	3	0
4	26	51	24	49	2	2
5	28	59	28	56	3	0
Total	**152**	**278**	**98.03%**	**95.68%**	**4.32%**	**1.97%**

Table 3 presents the variation of accuracy with the sampling frequency. At lower sampling frequency, the time resolution of the signal is not enough to quantify the movement accurately. Even though we have zero bit error at lower frequencies, accuracy is optimum at 50 Hz.

TABLE III. Accuracy of PLM Detection as a Function of the Sampling Frequency

Frequency	**Sensitivity**	**Specificity**	**Accuracy**
50 Hz	98.03	95.68	96.51
25 Hz	85.52	75.17	78.83
12.5 Hz	69.73	62.94	65.34

IV. Discussion

The primary objective was to show that it is possible to accurately quantify PLMs using two inertial sensors instead of the standard tibialis anterior EMG. Since we used multiple inertial sensors with a PSG system in this study, time synchronization became very important. Time warping was applied on the signal time values based on timestamps every minute to overcome the delay even in the range of milliseconds. Furthermore as we used a BTS link with a GATT profile to communicate with the two sensors, we had limitations in the allowable frequency of data streaming. As seen in Table 1, the best accuracy was at 50 Hz. We observed a significant loss of packets during wireless transmission and problem in long term streaming at higher sampling rate. This also depends on the packet size and the distance between the devices. Since sensor modules cannot be configured as slaves, due to the lack of global clock, the problem of synchronization arises. An adaptive DTW method was used to match the sequence in time where the previous minute unresolved delay was added to the next minute of operation. This result was verified by generating simultaneous motion of joint sensors, and applying synchronization algorithm to test synchronization. It can be clearly seen in Fig. 3 and 4 that only 3D accelerometer values would not be sufficient for the accurate quantification of PLMs. Even for false movement accelerometer values (Fig. 3) can have magnitude greater than the real PLM event accelerometer magnitude whereas quaternion rotation angle and the nature of rotation provide clear understanding about the real PLM event. The PLM algorithm can be further optimized by introducing new PLM detection parameters and by using other evolutionary techniques for classification.

V. Conclusion

Proposed system facilitates sleep studies and clinical diag-

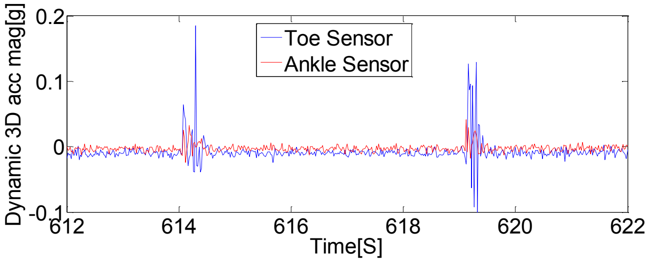

Figure 3a. Random PLM-like motion (3D accelerometer)

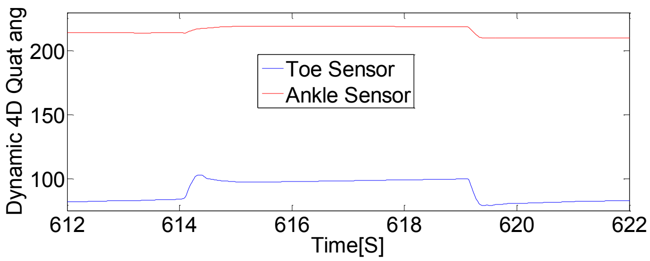

Figure 3b. Random PLM-like motion (4D Quaternion angle)

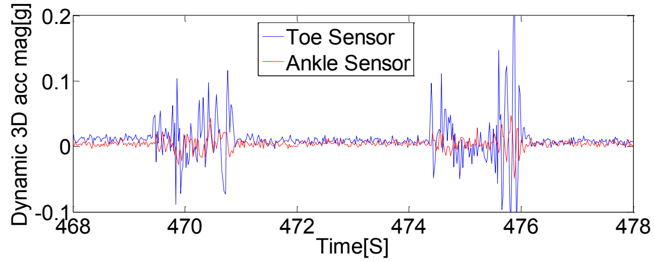

Figure 4a. PLM motion (3D accelerometer)

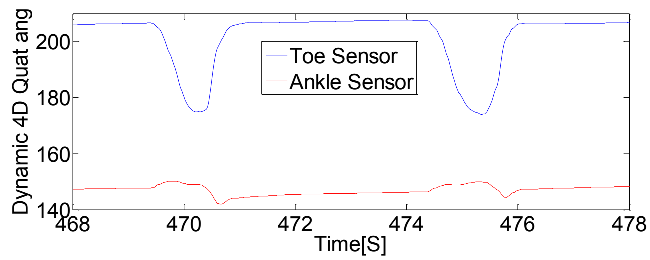

Figure 4b. PLM motion (4D Quaternion angle)

-nosis of insomnia using a hybrid WBAN. The synchronization technique using pulse generation is proven to be very precise and accurate. PLMs can be monitored using two inertial sensors on the toe and on the ankle which is effective and more convenient to the users. This is proven to be an alternative way of scoring PLMs other than using EMG. Future work is to optimize the detection method to further increase the accuracy of the PLM detection.

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