Wireless Body Area Sensor Network for Posture and Gait Monitoring of Individuals with Parkinson's Disease

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Abstract—This paper presents a wireless body area sensor network that detects and records real-time posture and gait kinematic data from individuals with Parkinson's disease. The network comprises wearable sensors placed at lower limbs and back of a human body to measure user's kinematics. The collected data are transmitted wirelessly to a receiver and stored in cloud-based database. The time series kinematic data is interpreted with adaptive fractal analysis (AFA) to differentiate a healthy subject from another with PD. We use frequency analysis to differentiate spontaneous movement from cued movement of clinical evaluations of several persons with Parkinson disease (PD).

Index Terms—Wireless sensors, body area network, gait, posture, Parkinson's disease, time series data analysis, frequency analysis

I. INTRODUCTION

Parkinson's disease (PD) is a degenerative disease of the nervous system that leads to tremors and difficulty with walking, movement and coordination [1], [2]. Persons with PD develop postural instability and disturbances in gait as the disease progresses. The lack of balance and gait control often leads to falling, injuries, dependence, and overall loss of quality of life [2]. Among the many symptoms of PD, freezing of gait (FoG) is a unique and disabling phenomenon. FoG is characterized by brief episodes of inability to step or by extremely short steps that typically occur on gait initiation or on turning while walking [3], [4]. FoG is a major cause for falling and injuries in persons with PD and it incurs significant healthcare costs in emergency visits and hospital admissions.

While a cure for PD is yet to be developed, physical rehabilitation has been successful at slowing disease progression, restoring independence, and maintaining quality of life [5]. Clinicians observe patients' performance in the clinic and make diagnosis based on data observed in clinic. However, it is unknown whether behavior observed in the clinical setting during rehabilitation accurately reflects spontaneous movement at home. We refer to the phenomenon that movements of persons with PD may present differently in clinic and at home as *white-coat performance*.

Advancements in sensor technologies coupled with miniaturization have made body area sensor networks applicable in many medical applications [6]–[8]. Body sensors (wearable, implantable or portable) are fast emerging as they are envisioned as a promising approach to monitoring both physiological conditions and disease progression. The ubiquitousness of the Internet enhances the connectivity of these sensors. A body area sensor network potentially enables monitoring of physiology without affecting the normal day-to-day life of patients. However, technical challenges remain to be conquered to make these systems acceptable by individuals. In this paper, we present the design of a wireless body area sensor network. We also discuss the research challenges in wireless sensor communication system design as well as energy efficiency.

The objective of the proposed wireless body area sensor network is to provide a non-intrusive device to measure, process, and model motion, activity of individuals with PD to understand their spontaneous movement in an un-observed environment.

In our proposed architecture, tiny body sensors are attached to lower limbs and back of the subject as shown in Fig. 1. The body sensors collect position and acceleration data in a periodic manner (with a sampling rate of 60-100Hz) and transmit them to a processing and storage node, which is implemented on a smartphone or other portable device. This node can store data and transfer the information to the doctor's office via telecom network or wireless local area network. To measure the posture change non-intrusively, we use low voltage flex sensors, pressure sensors, accelerometers and gyroscopes to build a networked sensor device that can be worn by a person to detect posture and gait changes. We apply adaptive fractal analysis and use frequency domain analysis to study the clinical data for cued and spontaneous movements. We show the difference of power spectral density with the cued and spontaneous data and demonstrate the hypothesized *white-coat effect*.

II. WIRELESS BODY AREA SENSOR NETWORK DESIGN

The proposed body area network sensing system has four components: sensing, networking, processing, and feedback. The proposed research activities aim at addressing the challenges in these areas to develop a non-intrusive wireless portable body area sensing system to understand the environmental, location, and activity variables when freezing of gait (FoG) occurs and close the loop with customized feedback to cue persons with PD to prevent FoG episodes. An overview of the system design is shown in Figure 1. Miniature sensors (accelerometer, gyroscope, magnetometer) are placed on the ankle, wrist, waist, and chest of a human body to measure kinematics of these body parts. These miniature sensors have small storage and limited computation power to perform complex data processing. To process data, sensors will send sensed data to a sink for processing through a wireless network. The sink, in the form of a special sensor node or a smartphone, will pre-process the collected data for compression and encoding and forward the processed data to a database through a wireless and wired access network. Data will be stored in the database and processed to identify features of the movement, activities, and FoG episodes. A feedback module will be implemented to provide necessary cues in a timely manner to the user when FoG is predicted.

Sensors. The sensor device includes a microcontroller, 3-axis accelerometer, 3-axis gyroscope, Zigbee transmitter, and a rechargeable lithium-ion battery as shown in Figure 2. The device can be placed on the lower back, ankles,
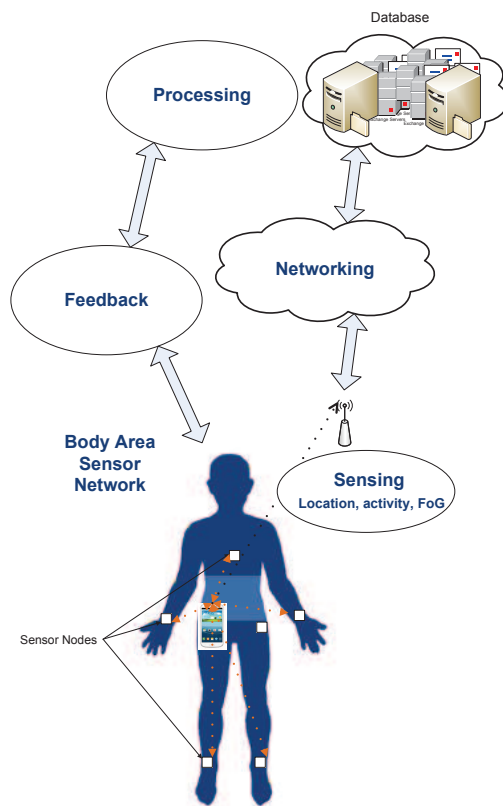

Fig. 1.   Wireless body area sensing network for individuals with PD.

thighs, and wrists of a person to collect acceleration and angular rotation data to associate to specific activities of daily living such as standing up, sitting down, and walking. Data from sensors are collected and stored on flash memory and also transmitted via a Zigbee transmitter to a computer hard-drive storage. The device is in the form of detachable sensor mote with a diameter of 5 centimeters.

Access network. We adopt the infrastructure of the existing networks (observation sensors that measure location, orientation, and possible environmental parameters). The access network is used to collect information from sensors where access points (APs) are used as sink nodes. The radio frequency of sensors is based on ZigBee (2.4 GHz). Sensors send the collected data at the programmed rate of 250 kpbs. The AP receives this data and stores it on a secure digital (SD) card. This card (and the saved information) can be carried to the clinic or data can be transmitted through a secure network. Consistent with our non-intrusiveness requirement, we consider network transmission of data as the ultimate means of data transport to relieve users from focusing on system setup and maintenance (sensors and other
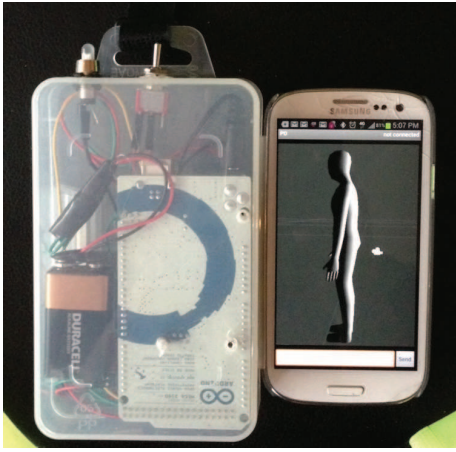
Fig. 2.   Sensor device and 3-D visualization feedback on a mobile device.

Fig. 3.   30-minute sensor data of sitting down to lying down.

equipment).

Data processing. The sensors are programmed with a sampling frequency in the 60-120 Hz range. The collected time series data (acceleration from accelerometer and angular rotation from gyroscope) are processed using fractal analysis through nonlinear adaptive filtering [9]. This method can readily remove non-stationarities from the signal, reduce noise more effectively than linear filters, wavelet denoising, and chaos-based noise reduction techniques; decompose a multiscale biosignal into a series of intrinsically bandlimited functions; and it offers a new formulation of fractal and multifractal analysis that is better than existing methods when a biosignal contains a strong oscillatory component, in this case the kinematic data on walking [10], [11].

Feedback. A visual feedback is implemented as a mobile application that displays the collected kinematics data and translates it to a 3-dimensional human model that can display the posture to the users as shown in Figure 2.

III. Experimental Results

The proposed wireless body area sensor network was tested on three healthy subjects (HS) and one subject with PD. The following activities were recorded from one sensor strapped on the chest of these subjects: sitting down, rising from a chair, walking and standing, lying down.

Figure 3 shows the time series data collected over a 30-minute period of a healthy subject from sitting to lying down. We observe that the original data is noisy when the subject was sitting but the trend from sitting to lying down is clearly observed around sample 60,000.
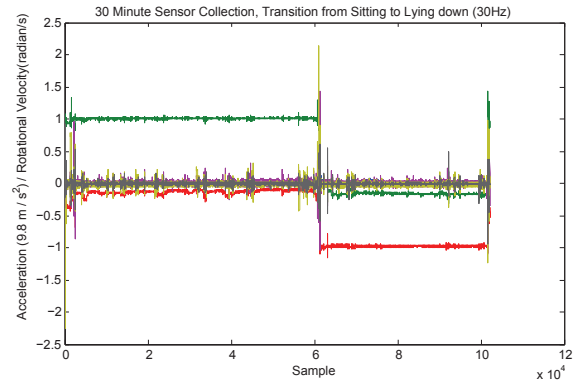
This type of time series data requires adaptive filtering to identify both global trend as well as local trends.

To observe the difference of gait and posture between healthy subject and subject with PD from the measured sensor data, the collected data are processed using fractal analysis through none linear adaptive filtering. We demonstrate the advantages of using fractal analysis through non-linear adaptive filtering with the kinematic data collected when subjects perform walking for a short period of time and using power spectral density to differentiate cued and spontaneous movements.

A. Adaptive fractal analysis

Adaptive fractal analysis (AFA) employs local linear or polynomial trends, with abrupt jumps around adjacent segments in a time series data [9]. The essence of this approach is to determine an optimal global trend based on patching best local polynomial fitting, where the "trend" can be identified without any prior knowledge. It also applies to complicated chaotic signals. Here we define a basic parameter, the window size w.

In fractal analysis, the Hurst exponent or Hurst parameter (H) is used as an indication of short-range or long-range memory or correlation. Depending on whether $0 < H < 1/2$, $H = 1/2$, $1/2 < H < 1$, the process is said to have anti-persistent, short-range, and persistent long range correlations, respectively.

The AFA follows the following steps:

- Identify a global trend signal to recreate local feature of the data using a simple polynomial function. This is to create a synthetic time series, $v(i), i = 1, 2, \cdots, N$, where N is the length (number of values) of the original time series signal.
  Partition the original time series signal, $u(i)$ into window of length $w = 2n + 1$.
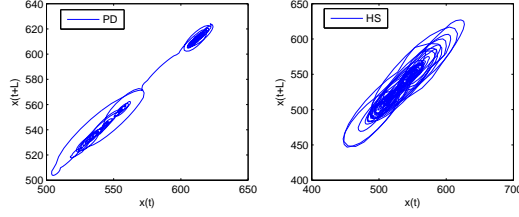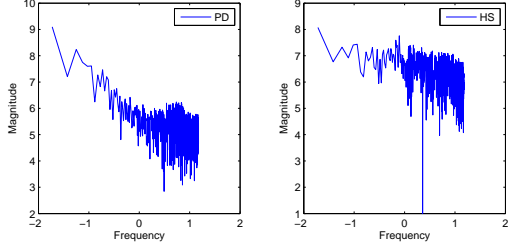
Fig. 5.   Phase diagram.

Fig. 7. $log_2 F(w)$ vs. $log_2 w$ curve for PD and HS.

Fig. 6. $1/f$ behavior on the high frequency.

Identify each window's best fitting polynomial of order M (we use polyfit order 1 or 2 in this paper). Stitch the local trend together $v(c)(l) = w_1 v(i)(l + n) + w_2 v(i+1)(l), l = 1, 2, ..., n + 1$, where $w_1 = [1 - (l-1)/n]$ and $w_2 = (l-1)/n$

- Detrend the data by removing the global trend signal that was just created to find the variance of the residuals of the fit. The residuals are computed using $u(i) - v(i)$ repeated for a range of w.
- Examine the relationship between the variance of the magnitude of the residual, $F(w)$, and the window size w.

$$F(w) = \left[\frac{1}{n} \sum_{i=1}^{n} (u(i) - v(i))^2 \right]^{1/2} \sim w^H \quad (1)$$

The trend signal is a low-frequency signal with cutoff frequency $f_w \sim 1/w\delta t$, where δt is the sampling time. The residual signal, which is the difference between the original signal and the trend signal, is a high-frequency signal, again with cutoff frequency f_w.

Figures 4-7 show our preliminary results on a short-period data collected from one sensor located at the ankle of the patients with PD using AFA.

From the time series measurement data in Figure 4, we can observe the difference of acceleration data in one axis of measurement between a subject with PD and a healthy subject. By examining more features in the frequency domain, such as phase, as shown in Figure 5 and high frequency behavior of the signal, as shown
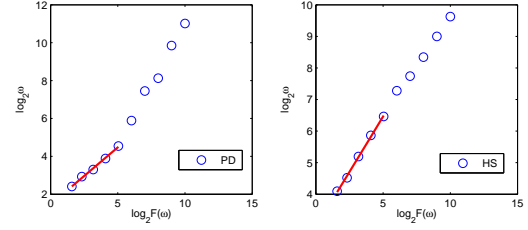
in Figure 6, we clearly observe the variance between a healthy subject and subject with PD. Although this preliminary data shows promising results in identifying the healthy subject and a PD patient using only one dimension acceleration data, the challenge remains to reduce data dimension and to explore efficient filtering methods for real-time processing.

B. Differentiate movement data with frequency domain analysis

The challenge of evaluating gait and posture for PD patients is to differentiate movement at different times of the day under different scenarios and environments such as before and after medication or rehabilitation sessions. We further evaluated the performance of the proposed system using AFA to process the data and compared the frequency-domain features to differentiate movement differences. The experiment data was collected in the clinic from five subjects with PD. The subjects were instructed to stand up from a chair, walk from the chair in a straight line, about 5 meters, and then turn around and sit back in the chair. Two sets of data were collected when the subjects were instructed by the clinician (referred as cued data) and were allowed to carry out the sequence without any instruction (referred as spontaneous data). We first detrended the data using AFA and then generated the power spectral density (PSD) of the detrended data. The time series data set includes acceleration, angular rotation speed, in the "x", "y", and "z" axises for the cued and spontaneous data set (7090 data records for cued movements and 7760 data records for spontaneous movements.), respectively. Here we extracted the data when the subject was walking and use the frequency-domain features, namely, PSD in the three axises to train and categorize cued and spontaneous movements.

We observe that using PSD of the observed acceleration data in three axises as features is sufficient to differentiate cued and spontaneous movement. The scattered plot of the PSD for cued and spontaneous
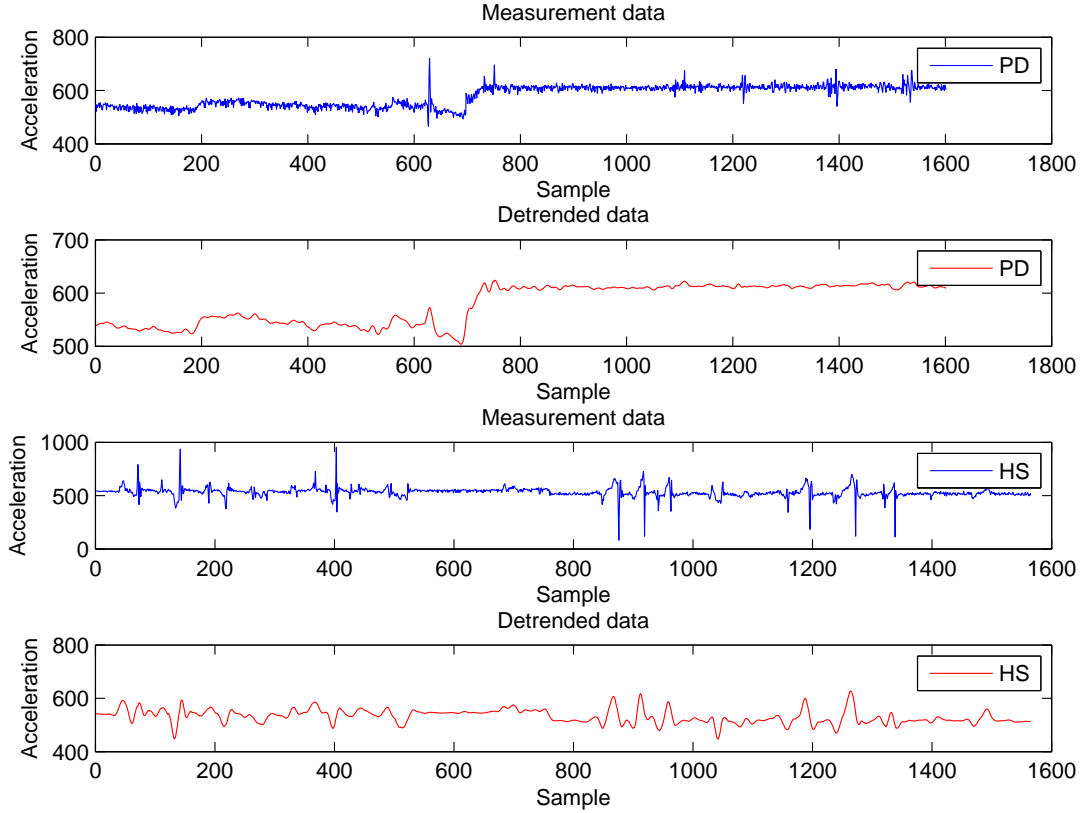
Fig. 4. Time series data, measured data vs. detrended data, PD vs. HS.

walking data is shown in Figure 8. We observe that for the cued movements, the frequency components are more spread out than the spontaneous movements. This indicates that a cued movement has more disturbances than a person's natural movement, which resulting in larger number of frequency components. This clearly shows the impact of *white-coat phenomenon*.

Figure 9 shows the PSD of the cued and spontaneous movement of one subject. We do not observe a big change in the frequency components due to the fact that the same person performed the same movement. However, we can see a clear difference in the amount of the energy observed in the frequency components of the data observed in each axis. This further shows that the movement of subject varies when they were cued and were not cued. We observe similar trends for all five subjects in this study.

C. Discussion and Future Work

The validity of the adaptive fractal analysis method relies on being able to locally represent a continuous time
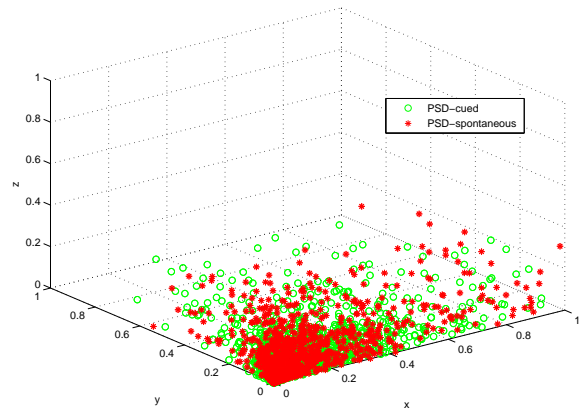

Fig. 8. Power spectral density of the measured acceleration data for cued vs. spontaneous movement.

function by its Taylor series. It requires high sampling rate of the continuous time signal. However, body area sensor network devices are required to be small in size,

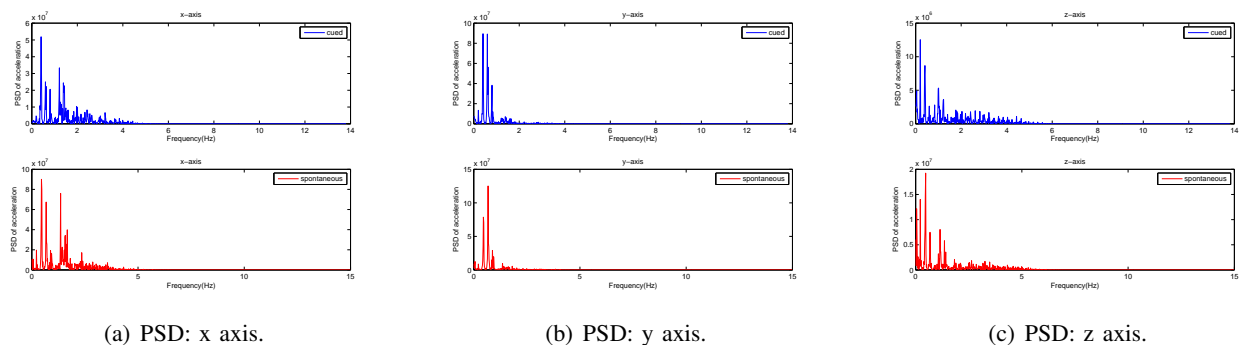(a) PSD: x axis.　　　　　(b) PSD: y axis.　　　　　(c) PSD: z axis.

Fig. 9.　Power spectral density comparison of cued vs. spontaneous movement of one studied subject.

power efficient, and connected wirelessly to achieve unobtrusive monitoring. Therefore, many commercial inertial sensing devices, their signal processing system often have very limited sampling rate to preserve battery life. Being able to quantifying the kinematic data between different subject and for one subject under different conditions (e.g. medication and treatment history) remains a challenging task for future research.

IV. Conclusions

In this paper, we presented an approach for the continuous monitoring of the motion of limbs of patients with Parkinson's disease. The approach is based on wearable sensors supported by wireless transmitters to forward collected data to storage for data analysis. The wireless transmission is based on IEEE 802.15.2, also known as ZigBee. The time series kinematic data is interpreted with adaptive fractal analysis (AFA) to differentiate a healthy subject from another with PD. We apply AFA to data collected by our developed sensors in preliminary trials and the data analysis shows motion with different patterns for healthy and PD patients. We demonstrated the potential impact of white-coat phenomenon with a set of movement data when the subject is cued vs. spontaneous movements by comparing the power spectral density of both sets of data. It is expected that different patients present a diverse set of motion patterns. The data is expected to be submitted to further analysis for the detection of unique PD signatures after a further trials are performed with a larger set of patients.

V. Acknowledgments

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