Home Monitoring of Patients with Parkinson's Disease via Wearable Technology and a Web-based Application

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Abstract—Objective long-term health monitoring can improve the clinical management of several medical conditions ranging from cardiopulmonary diseases to motor disorders. In this paper, we present our work toward the development of a home-monitoring system. The system is currently used to monitor patients with Parkinson's disease who experience severe motor fluctuations. Monitoring is achieved using wireless wearable sensors whose data are relayed to a remote clinical site via a web-based application. The work herein presented shows that wearable sensors combined with a web-based application provide reliable quantitative information that can be used for clinical decision making.

I. INTRODUCTION

CLINICAL management of a large number of medical conditions requires extensive monitoring of a person's health status. Intermittent hospital monitoring, which provides only a brief window into the health of a person, might miss trends that can lead to early detection of a problem [1]. With current and on-going advances in sensor technology it becomes possible to envision an unobtrusive system for monitoring human health on a more continuous basis [2]. Such sensor systems are promising tools that can enable long-term monitoring in the home. Home monitoring has the potential to improve the standards of healthcare delivery while making it an efficient and cost effective process. Herein we present our work toward the development of a general purpose remote monitoring system

that can be used for home monitoring of patients with different conditions. In addition, we present results of our analyses of data recorded using such home-monitoring system from patients with Parkinson's Disease (PD). Our analyses show that the system can be used to effectively monitor the severity of motor fluctuations in patients with PD. These results make a strong case for the feasibility of home monitoring of patients with late stage PD who are known to require periodic titrations of their medications.

II. PARKINSON'S DISEASE

A. Overview

PD is the most common disorder of movement, affecting about 3% of the population over the age of 65 years and more than 500,000 US residents. The characteristic motor features are development of rest tremor, bradykinesia, rigidity, and impairment of postural balance. Current therapy of PD is based primarily on augmentation or replacement of dopamine, using the biosynthetic precursor levodopa or other drugs, which activate dopamine receptors. These therapies are often successful for some time, but most patients eventually develop motor complications. Complications include *wearing off*, the abrupt loss of efficacy at the end of each dosing interval, and *dyskinesias*, involuntary and sometimes violent writhing movements [3,4]. The severity of motor complications varies over time in association with medication dosages. Clinicians refer to such variations as motor fluctuations (Fig. 1). Motor fluctuations become severe in late stage PD thus requiring frequent titration of medications.

B. Monitoring Motor Fluctuations

Currently available tools for monitoring motor fluctuations are quite limited. In clinical practice, information about motor fluctuations is usually obtained by asking the patient to recall the number of hours of ON and OFF time they have experienced in the recent past. "ON time" is used to refer to periods when medications are
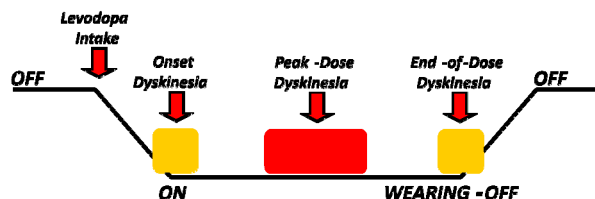
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Fig. 1 Parkinson's disease motor fluctuation cycle.

effective in attenuating symptoms. "OFF time" is used to refer to periods when symptoms are present. This kind of self-report is subject to both perceptual bias and recall bias. A reliable quantitative tool to monitor motor complications in PD patients would be valuable both for routine clinical care of patients as well as for trials of novel therapies.

In this study, we explored the use of wearable sensors to capture movement features that are associated with changes in the severity of motor fluctuations as they occur during the intervals between medication dosages. Our aim was to identify movement characteristics associated with motor fluctuations in patients with PD by relying on wearable sensors [5]. We used 8 accelerometers on the upper and lower limbs to monitor patients while they performed a set of standardized motor tasks from the Unified Parkinson's Disease Rating Scale (UPDRS). A video recording of the subjects was performed which was used later by an expert clinician to assign clinical scores. We also investigated the computational costs associated with extracting features on the sensor nodes as such an approach would be advantageous in terms of extending battery life and reducing storage requirements.

III. System Requirements

There are several challenges associated with monitoring patients in the home [6]. Monitoring applications range in purpose from tracking activity for wellness management to detecting in real-time the occurrence of epileptic seizures. System requirements will differ based on the nature of the application at hand. The hardware requirements for a typical home monitoring system can be broken down into three categories (1) sensor network, (2) data security, and (3) clinician-patient interaction.

A. Sensor Network

A typical wireless body sensor network (BSN) consists of several miniature sensors with limited resources such as storage, bandwidth, processing power and battery capacity. As shown in Fig. 2, the sensors relay data to a base station, such as a laptop or mobile phone, which acts as an information gateway. One of the key challenges of a BSN is to efficiently manage available resources so that high data quality is maintained while achieving long battery life. Achieving this goal requires careful management of the radio, storage and on-board processing. An effective BSN would intelligently manage and modulate the activity on the sensor nodes to meet the target battery life and data quality.

B. Data Security

Securing the data within a BSN and as it travels from the patient to the clinician is of outmost importance. This involves ensuring that a secure communication channel is established for data transfer that meets the established regulations for data security and patient privacy.

C. Clinician-Patient Interaction

Interaction between patients and clinicians is critical to the success of a home monitoring application. The requirements could range from simple video conferencing to real-time access to the sensor data. Some applications, such as detection of epileptic seizures or fall detection, require real-time data analysis, reporting of events and prompt intervention by a clinician. Appropriate data processing procedures must be available to derive clinically-relevant information from the analysis of wearable sensor data. Most desirable are applications that provide clinicians with information in the format of clinical scores capturing the severity of the condition that affects patients undergoing monitoring (e.g. the severity of Parkinsonian symptoms).
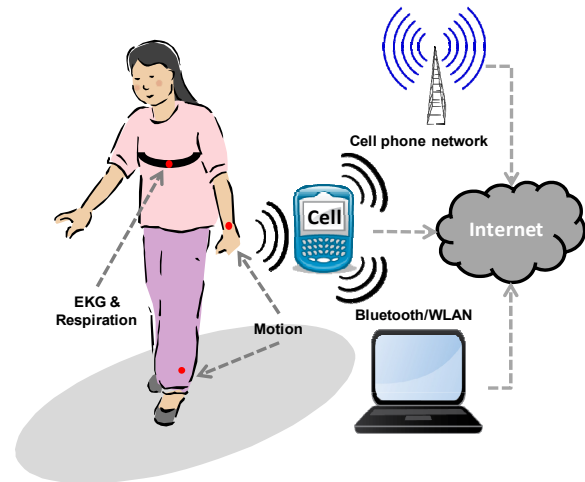

Fig. 2 General home monitoring scenario. Wearable sensors record data that is sent over the Internet via gateways such as mobile phones, PDAs, and personal computers.

IV. System Design and Implementation

We developed a system designed to address the above-described system requirements. The system relies upon a system architecture that enables home monitoring of patients with PD, but also other medical conditions. We leveraged previous work by our team that led to the Mercury BSN platform. The interaction between patient and clinician is enabled via a web-application that provides access to sensor data and video conferencing capability. Finally, algorithms were developed for the specific application at hand, i.e. monitoring the severity of motor fluctuations in patients with late stage PD. The algorithms estimate scores that match those achieved via the UPDRS.

A. System Architecture

The implemented home-monitoring system shown in Fig. 3, involves software services running at three tiers: central portal server, patient's hosts, and clinician's hosts. To ensure both data security and high availability of the remote health monitoring service, a well-provisioned central portal server provides a secure and reliable central location for coordinating real-time data collection and video services. The portal server resides in a secure healthcare provider data

center and allows access only over securely encrypted services. Our implementation uses SSL and SSH for establishing secure channels for all data transfer. Using the secure channels, both patient's and clinician's software clients rely on the database, web server, video conferencing service and a live data forwarding service to perform background data logging and live interactive sessions. Each patient's host, usually a laptop, typically resides in a home network and runs the Mercury BSN platform. The platform collects motion data and continuously uploads sensor data to the database at the central portal server. On the clinician's host, residing in the clinician's office or home, only a web browser is required to access the services.
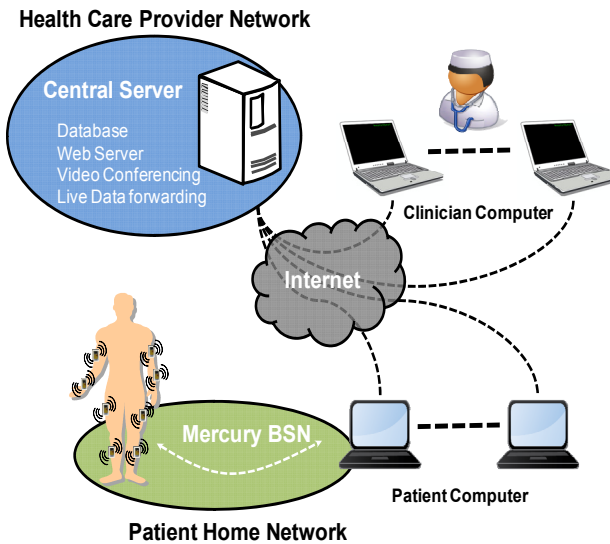

Fig. 3 An overview of the architecture of proposed monitoring system.

B. Mercury Platform

The wireless BSN platform developed by our team, is called Mercury [7]. Mercury consists of a number of tiny, wearable wireless sensors based on the SHIMMER sensor platform and has been designed to support long-term, longitudinal data collections on patients in the hospital and home settings and to overcome the core challenges of long battery lifetime and high data fidelity for long-term studies where patients wear sensors continuously 12 to 18 hours a day. This requires tuning sensor operation and data transfers based on energy consumption of each node and processing data under severe computational constraints. Mercury provides a high-level programming interface that allows a clinical researcher to rapidly build up different policies for driving data collection and tuning sensor's battery life.

C. Web-Application and Data Analysis

Besides collecting, storing and securely providing patient motion data, our system also supports live video communication capability between clinicians and patients. Using the video interaction feature, clinicians can remotely conduct supervised data collection sessions that are typically done in a hospital environment today. This video interaction service is provided by a Red5 video conferencing server. To provide a user-friendly interface, we implemented a cross-platform web-application, MercuryLive (shown in Fig. 4), which runs as a Flash plug-in to any modern web browser. This application contains a GUI to display live decimated motion signals alongside the video session to allow clinicians to view and annotate data during each remote supervised data collection session. Using MercuryLive, the clinicians can also download long-term data to allow customized rigorous analyses on the data.

Data collected using the above-described system are then processed to derive estimates of UPDRS scores. Accelerometer data collected using the Mercury platform are segmented, filtered, and processed to derive features associated with movement characteristics of interest (e.g. the periodic component from 4 to 7 Hz associated with tremor) [5]. A Support Vector Machine (SVM) classifier was trained and optimized for the classification of clinical scores for dyskinesia, bradykinesia and tremor. The classifier is trained using datasets recorded while subjects perform motor tasks that are part of the UPDRS assessment. Training of the algorithm aims at achieving estimates of clinical scores provided by a neurologist observing patients while performing the same motor tasks (that are part of the UPDRS assessment). In other words, the analysis of wearable sensor data gathered using the above-described home-monitoring platform allows one to achieve automatic analysis of data to perform remotely a UPDRS assessment. Our analysis focused on deriving an appropriate window length for feature extraction and understanding the impact of different features and their combinations on classification accuracy.

V. RESULTS

Field-tests of the platform showed that the system can be effectively used to gather data from patients with PD to assess the severity of symptoms and motor complications
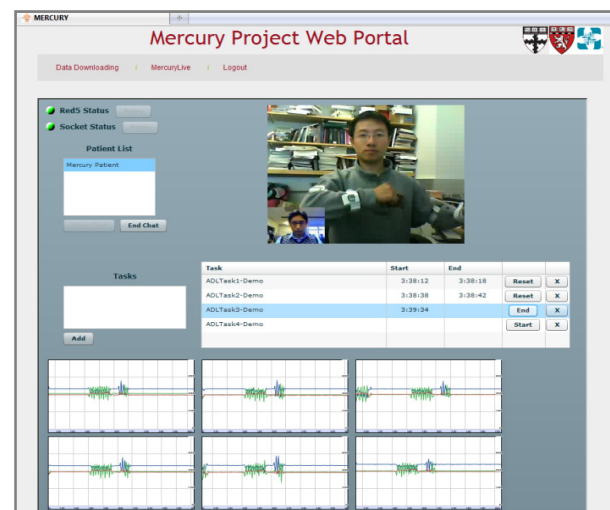

Fig. 4 Screen shot of the MercuryLive web-application.

during motor fluctuation cycles.

Encouraging results were obtained from the analysis of wearable sensor data. Extensive assessments were performed to optimize the algorithms. The classification error generally decreased by increasing the window length used to perform feature extraction. We tested window lengths ranging from 1 s to 7 s in increments of 1 s. The classification error was approximately 5% for tremor, bradykinesia and dyskinesia for a window length of 5 s. Increasing the window length beyond 5 s did not yield significant improvements in the classification performance. Also, we observed that shorter window lengths (~1-2 s) were suitable for tremor. This is not surprising as the signal of interest typically ranges between 4 Hz and 7 Hz. Conversely, dyskinesia and bradykinesia required longer data segments (~3-5 s). We tested three different kernel implementations (polynomial, radial basis and exponential) for the Support Vector Machine (SVM) classifier. A third-order polynomial kernel, with the misclassification cost parameter C = 10, performed better than the other tested kernels for all three target symptoms and motor complication (tremor, bradykinesia and dyskinesia).
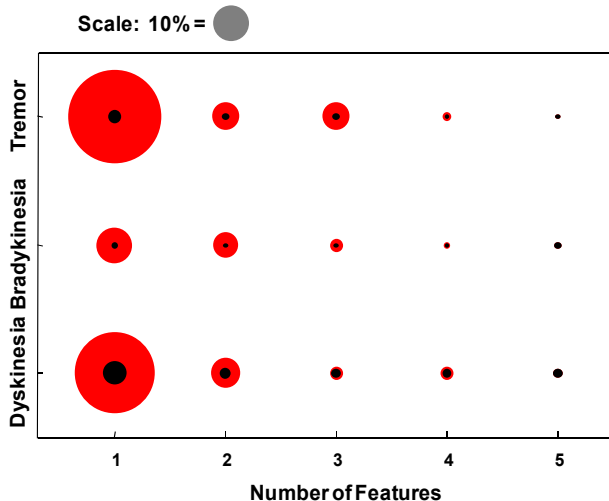

Fig. 5 Best (black) and worst (red) case classification error (%) for different feature combinations.

An important aspect of our analysis was the study of the relationship between different feature types and their impact on the classification performance. To perform this assessment, we performed analyses using all possible combinations of features using a SVM with a third-order polynomial kernel (C = 10) and a window length of 5 s. In Fig. 5, we can see best case and worst case results when considering different combinations of features. For tremor, we obtained a classification error of 6.6% using a single feature (signal entropy). When we used two features (RMS and data range) the error was around 3%. For bradykinesia, using frequency-based features and data range we obtained an error of around 2.5%. For dyskinesia, we achieved a classification error of 3.7% using the signal entropy feature

and of 1.9% using the cross-correlation and signal entropy features.

From our studies to estimate the computational cost of performing feature extraction on the BSN nodes, we found that signal entropy and cross-correlation features were the most computationally expensive while data range and RMS value were the least computationally expensive. Our results indicate that it would be possible to perform efficient feature extraction on the BSN nodes using data range, RMS value and frequency-based features. The classification error when using these three features were 3.4% for tremor, 2.2% for bradykinesia and 3.2% for dyskinesia.

VI. Conclusions

The work herein presented shows that a home-monitoring system that leverages wireless, wearable sensor technology and a web-based application can be relied upon to gather clinically relevant information for the management of patients with late stage PD. Our results demonstrate that clinical scores that measure the severity of symptoms and motor complications can be reliably estimated using algorithms for the analysis of wearable sensor data. The system has the potential to simplify the process of monitoring the effectiveness of the medication regimen and of titrating medications when deemed necessary.

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