Advances in Wearable Technology for Rehabilitation

Paolo BONATO\textsuperscript{a,b}
\textsuperscript{a}Department of Physical Medicine and Rehabilitation, Harvard Medical School, Spaulding Rehabilitation Hospital, Boston MA, USA
\textsuperscript{b}Harvard-MIT Division of Health Science and Technology, Cambridge MA, USA

Abstract. Assessing the impact of rehabilitation interventions on the real life of individuals is a key element of the decision-making process required to choose a rehabilitation strategy. In the past, therapists and physicians inferred the effectiveness of a given rehabilitation approach from observations performed in a clinical setting and self-reports by patients. Recent developments in wearable technology have provided tools to complement the information gathered by rehabilitation personnel via patient’s direct observation and via interviews and questionnaires. A new generation of wearable sensors and systems has emerged that allows clinicians to gather measures in the home and community settings that capture patients’ activity level and exercise compliance, the effectiveness of pharmacological interventions, and the ability of patients to perform efficiently specific motor tasks. Available unobtrusive sensors allow clinical personnel to monitor patients’ movement and physiological data such as heart rate, respiratory rate, and oxygen saturation. Cell phone technology and the widespread access to the Internet provide means to implement systems designed to remotely monitor patients’ status and optimize interventions based on individual responses to different rehabilitation approaches. This chapter summarizes recent advances in the field of wearable technology and presents examples of application of this technology in rehabilitation.

Keywords. wearable technology, wireless communication, e-textile, telemedicine

1. The State of the Art in Wearable Technology

Significant progress in computer technologies, solid-state micro sensors, and telecommunication has advanced the possibilities for individual health monitoring systems. A variety of compact wearable sensors are available today and we expect that more will be available in the near future. This technology has allowed researchers and clinicians to pursue applications in which individuals are monitored in the home and community settings [1].

Figure 1 shows a schematic representation of a wearable system as it can be envisioned based on currently available wearable technology. A combination of wireless sensors and sensors embedded in the person’s garments (e.g. a sensor suit) are utilized to monitor data such as heart rate, respiratory rate, and movements of the limbs. A data logger (e.g. a personal digital assistant, a cell phone) is utilized to store data and transmit data and alerts to a remote clinical center or a caregiver according to the application of interest. Clinical personnel have remote access to the monitoring system,
To order a book contact by fax or by e-mail the offices below:

Gazelle Book Services Ltd
White Cross Mills
Hightown
Lancaster LA1 4XS
United Kingdom
Tel.: +44 1524 68765
Fax: +44 1524 63232
sales@gazellebooks.co.uk

Advanced Technology in Rehabilitation
Empowering Cognitive, Physical, Social and Communicative Skills through Virtual Reality, Robots, Wearable Systems and Brain-Computer Interfaces
Volume 145 Studies in Health Technology and Informatics
June 2009, approx. 310 pp., hardcover
Price: US$167 / £115 / £81

Enacting Intersubjectivity
A Cognitive and Social Perspective on the Study of Interactions
Edited by: F. Morganti, A. Carassa and G. Riva
May 2008, approx. 280 pp., hardcover
Price: US$161 / £115 / £81

From Communication to Presence
Cognition, Emotions and Culture towards the Ultimate Communicative Experience
Festschrift in honor of Luigi Anolli
Edited by: G. Riva, M.T. Anguera, B.K. Wiederhold, F. Mantovani
September 2006, 323 pp., hardcover
ISBN: 978-1-58603-662-1
Price: US$161 / £115 / £81

Global Data Management
Volume 8 Emerging Communication: Studies on New Technologies and Practices in Communication
Edited by: R. Baldoni, G. Cortese, F. Davide and A. Melpignano
July 2006, 376 pp., hardcover
Price: US$161 / £115 / £81

The Hidden Structure of Interaction
From Neurons to Culture Patterns
Volume 7 Emerging Communication: Studies on New Technologies and Practices in Communication
Edited by: L. Anolli, G. Riva, S. Duncan Jr. and M.S. Magnusson
May 2005, 304 pp., hardcover
Price: US$161 / £115 / £81

Ambient Intelligence
The Evolution of Technology, Communication and Cognition Towards the Future of Human-Computer Interaction
Edited by: G. Riva, F. Vatalaro, F. Davide and M. Alcântara
January 2005, 316 pp., hardcover
Price: US$161 / £115 / £81

Being There
Concepts, Effects and Measurements of User Presence in Synthetic Environments
Edited by: G. Riva, F. Davide and W.A. IJsselsteijn
2003, 344 pp., hardcover
Price: US$161 / £115 / £81

Say not to Say: New Perspectives on Miscommunication
Edited by: L. Anolli, R. Ciceri and G. Riva
2001, 288 pp., hardcover
Price: US$161 / £115 / £81

Towards CyberPsychology
Mind, Cognition and Society in the Internet Age
Edited by: G. Riva and C. Galimberti
2001, 326 pp., hardcover
ISBN: 1-58603-197-x
Price: US$161 / £115 / £81

Communications Through Virtual Technologies
Identity, Community and Technology in the Communication Age
Edited by: G. Riva and C. Galimberti
2001, 326 pp., hardcover
ISBN: 1-58603-197-x
Price: US$161 / £115 / £81
for instance, via a web-based application. The system is recharged at night via a docking station that allows for fast communication with a remote clinical center by means of an access point thus facilitating transfer of raw data and the performance of maintenance tasks. This technology is bound to enable new telemedicine applications [2] and to facilitate the implementation of the medical home concept [3].

Wearable devices can be divided into two categories: 1) garments with embedded sensors and 2) body sensor networks. The idea of embedding sensors into garments was first pursued by a research team at Georgia Institute of Technology led by Dr. Sundaresan Jayaraman [4, 6]. Research work by this team eventually led to a product referred to as **Smart Shirt** (Figure 2). The **Smart Shirt** is a wearable health monitoring system by Sensatex, Inc., USA (http://www.sensatex.com/) that monitors heart rate, body temperature, and motion of the trunk. The monitoring system is designed as an undershirt with various sensors embedded within it. Data are transmitted to a pager-size device attached to the waist portion of the shirt where it is sent via a wireless gateway to the Internet and routed to a data server where the actual monitoring occurs. The **Smart Shirt** incorporates a patented technology named “Wearable Motherboard” which incorporates optical fibers, a data bus, a microphone, other sensors, and a multifunction processor, all embedded in a basic textile grid that can be laundered.
Figure 2. The Smart Shirt by Sensatex, Inc., USA. a garment with embedded sensors for physiological function monitoring. (Reproduced with permission)

Figure 3. The MIRhl is a platform of sensors and wearable computing technology to gather data in the field. A description of the platform can be found at http://www.media.mit.edu/wearables/mirhl/. (Reproduced with permission)
Following the pioneer work by the research team at Georgia Institute of Technology, several companies and research groups pursued the development of garments with embedded sensors. An example of the technology developed by companies that manufacture wearable systems is the LifeShirt, by VivoMetrics. The LifeShirt is a comfortable, washable “shirt” that contains numerous embedded sensors that continuously monitor 30+ physiological signs of sickness and health. The list of physiologic functions it monitors includes: ECG, respiration, BP, PO$_2$, and posture.

Data from the sensors are recorded to a small belt-worn recorder where it is encrypted and sent to VivoMetrics Data Center by cellular telecommunication. There it is decrypted, scanned for artifacts, and posted in a database where summary reports can be generated for the client.

In the research arena, several groups distinguished themselves for the originality of their contributions. Among others, Dr. Sandy Pentland at Massachusetts Institute of Technology developed the MIThril, [7, 9] an architecture that combines hardware and software platforms as shown in Figure 3. The hardware combines computational, sensing and networking in a clothing-integrated design. The software is a combination of user interface elements and machine-learning tools built on the Linux operating system. This architecture has been used by several mobile platforms for personal digital assistants and cell phones to demonstrate that active pattern analysis of face-to-face conversations and interactions within the workplace have the potential to improve the functioning of the organization [10]. Researchers in Dr. Pentland’s laboratory are currently exploring potential clinical applications of this technology.

Other examples of garments designed to monitor physiological functions are those developed by Dr. Danilo De Rossi’s group at University of Pisa [11, 13] and Dr. Harry Asada at Massachusetts Institute of Technology [14, 15]. These garments specifically address the need for monitoring patients’ movements. However, as with all garment-based solutions, they require patients to wear a special clothing item. While we believe that this approach is necessary for very long-term monitoring (i.e. months to years), we see the use of miniature wireless sensors as more practical when monitoring needs to be achieved over shorter periods of time (i.e. a few days to a week).

Seminal work was performed toward the development of wearable wireless sensors at the NASA’s Jet Propulsion Laboratory, Pasadena, CA where researchers attempted to implement prototypes of sensor patches to record physiological data over extended periods of time [16-18]. These non-invasive sensors were miniature biotelemetric units resembling adhesive bandages (Figure 4). They were designed to communicate with a hand-held unit (i.e. readout unit). The patches contained a noninvasive microelectromechanical sensor integrated with electronic circuitry that transmitted a radio signal modulated by the processed sensor output. The patch did not contain a battery. Instead, it contained a circuit for extracting power from an incident radio beam that was present during readout. For readout, a hand-held radio transceiver was positioned near the patch; the transceiver transmitted the radio beam to the patch circuitry and received the modulated radio signal transmitted from the patch. These sensors were proposed for use in measuring temperature, heart rate, blood pressure, and other physiological parameters. Following this exciting work, NASA initiated the Sensors 2000! program to develop advanced sensors, biotelemetry systems, and data systems technology, including the Sensor Pill, that can be swallowed to monitor the health status of the alimentary canal and other organ systems.
In the business sector, several companies took inspiration from the seminal work achieved by researchers at NASA’s Jet Propulsion Laboratory and developed systems based on body sensor networks for commercialization. Among others, FitLinxx [http://www.fitlinxx.com/brand.htm] has recently put on the market an ultra-low-power wireless personal area network that provides two-way radio communication that can control and respond to sensors and actuators, as well as provide wireless connectivity to the Internet via devices such as a cell phone, personal digital assistant or PC. Based on this platform, FitLinxx has developed products for health monitoring that integrate heart rate, blood pressure, a pedometer, and body weight data gathered using a special weight scale. Similar products are offered by BodyMedia Inc [http://www.bodymedia.com/]. BodyMedia’s products are centered on the SenseWear Armband, a sleek, wireless, wearable body monitor that enables continuous physiological and lifestyle data collection outside the lab environment. Worn on the back of the upper arm, it utilizes a unique combination of sensors and technologies that allows one to gather raw physiological data such as movement, heat flow, skin temperature, near body ambient temperature, heart rate, and galvanic skin response.

The SenseWear Armband contains a 2-axis accelerometer, temperature sensors for monitoring heat fluctuation, skin temperature, near body ambient temperature, galvanic skin response, and heart rate received from a Polar Monitor system. The SenseWear Armband can be worn continuously up to 3 days without recharging the battery (at default sampling rate settings), and stores up to 5 days of continuous physiological and lifestyle data. Research software is available to offer audio and tactile feedback for reminders, targets, and alerts. Its ability to provide 2-way communication makes the SenseWear Armband a hub for collecting data from other third-party products such as a weight scale or a blood pressure cuff. The manufacturer promotes the product as “eliminating the need for researchers and clinicians to administer and apply cumbersome sensors to their research subjects.”

The research and development work summarized above is bound to facilitate the development of new clinical applications in telemedicine [2]. However, a fundamental limitation that hinders the application in rehabilitation of all commercially available systems and the majority of the body sensor networks developed in the research field is that most of the available systems are only suitable for managing data gathered at a sampling rate of a few Hz per channel. The ideal sampling rate for applications in
rehabilitation ranges from 100 Hz for biomechanical data to 1 kHz for surface EMG data. To our knowledge, only two research groups have focused on the development of body sensor networks with the performance required by clinical applications in rehabilitation. Dr. Emil Jovanov at University of Alabama [16] and Dr. Matt Welsh at Harvard University [17, 18] developed body sensor networks that provide adequate performance for application in rehabilitation. These groups developed complex data management architectures with buffering and data transmission that occurs both in real time as well as offline to meet the specifications of applications in rehabilitation. The approaches developed by these researchers achieve high bandwidth in ways compatible with the low-power consumption specification that needs to be met in order to allow one to implement a wearable system for monitoring patients over days.

Researchers and clinicians with a focus on rehabilitation are demonstrating a growing interest in the adoption of wearable technology when monitoring individuals in the home and community settings is relevant to optimize outcomes of rehabilitation interventions. Three major categories of application of wearable technology are emerging: 1) with the focus on monitoring motor activities via pedometers or sensor networks that go beyond the use of simple pedometers; 2) with the emphasis on medication titration and, more generally, applications in which the severity of symptoms (e.g. in motor disorders) is assessed and a clinical intervention is adjusted accordingly; and 3) with the focal point on the assessment of the outcomes of therapeutic interventions (i.e. physical and occupation therapy) with potential for gathering information suitable to adjust the intensity and modality of the prescribed therapeutic exercises. The following three sections summarize recent work by our team and others in the above-described three areas of development of new applications of wearable technology in rehabilitation.

2. Monitoring Motor Activities in Patients with COPD

Chronic obstructive pulmonary disease (COPD) is a major public health problem. COPD is currently the fourth leading cause of death in the world [19], and is projected to rank fifth in 2020 as a worldwide burden of disease [20]. Disability, hospitalizations, and medication costs associated with this disease account for 15 billion dollars in lost revenues and health care expenditures annually, an estimated 16% of the national health care budget [21]. Despite the increasing numbers of patients with COPD, there has been little advancement in the ability of healthcare providers and clinical researchers to monitor patients with COPD. The forced expiratory volume in 1 s (FEV$_1$), long thought to be the gold standard, has been shown to correlate poorly with other measures of disease status and does not predict mortality and resource utilization. In the research setting, the FEV$_1$ takes too long to change to be an efficient and meaningful outcome measure. Recent work by our team [22] and others [23, 24] has focused on the hypothesis that measurement of cumulative free-living physical activity with wearable technology in the patient’s home environment combined with physiological data collection (heart rate, respiratory rate, and oxygen saturation) can complement current clinical assessments of disease status and provide improved monitoring of COPD patients.

In recent work by our team [22] we studied 6 males and 6 females, mean age 68 ± 11 years, with severe COPD. Mean ± s.d. FEV$_1$ was 0.96 ± 0.51 L (34 ± 17% predicted) and FVC 2.57 ± 0.91 L (70 ± 18% predicted). At the time of monitoring, the
average six-minute walking distance was 1170 ± 304 feet. In Part I of this pilot study, our aim was to automatically identify three exercises comprising the aerobic portion of the pulmonary rehabilitation exercise program from a continuous data record: walking on a treadmill, cycling on a stationary bike, and cycling of the upper extremities on an arm ergometer. Identification was based on the output of a neural network trained with examples of accelerometer data corresponding to each of the exercise conditions. We demonstrated that accurate and reliable identification of the exercise activities could be achieved, thus enabling monitoring of patients’ compliance with a prescribed exercise regimen outside of the rehabilitation environment. For misclassification equal to 5%, the sensitivity of the classifier was remarkably high, ranging from 93 to 98% across subjects. Details concerning the study are provided in Sherrill et al [25] and Moy et al [26].

In Part II of this preliminary investigation, we extended the protocol to include typical activities such as climbing stairs, walking indoors, doing household chores, etc. Identifying these types of activities is relevant for assessing patients’ overall mobility.

We collected data by providing patients with a script as described in Sherrill et al [22]. Due to the physical limitations of the COPD individuals, it was not feasible to gather more than a minute of data for tasks such as ascending stairs. Since the number of features derived from the accelerometer data far exceeded the number of data segments available, a neural network approach was not considered to be appropriate. We envisioned therefore compiling data from a large group of patients and performing all identifications based on an existing database of examples rather than custom-training the classifier for each individual. In order for this to be a workable solution, the variability across tasks must exceed the variability within tasks due to different individuals. To show that this was a feasible approach, we sought ways to visualize the relationships among clusters of data points corresponding to the conditions of interest. We combined principal components analysis (PCA) and Sammon’s mapping. First, a PCA transformation was applied, and the first 15 PCs (accounting for 90% of the total variance) were retained. Then, the Sammon’s map was computed on the transformed data. Results were viewed as a scatter plot, color-coded by task as shown in Figure 5 utilizing a gray scale. A clear division is evident among tasks. Techniques to assess the “quality” of the clusters were then utilized as reported in Sherrill et al [22], thus allowing us to conclude that the motor activities of interest can be classified based on accelerometer data recorded from upper and lower extremities.
3. Medication Titration in Individuals with Parkinson’s Disease

Parkinson’s disease is the most common cause of movement disorder, affecting about 3% of the population over the age of 65 years and more than 500,000 US residents. The characteristic motor features of Parkinson’s disease include the development of rest tremor, bradykinesia (i.e. slowness of movement), rigidity (i.e. resistance to externally imposed movements), and impairment of postural balance. The primary biochemical abnormality in Parkinson’s disease is deficiency of dopamine due to degeneration of neurons in the substantia nigra pars compacta. Current therapy of Parkinson’s disease is based primarily on augmentation or replacement of dopamine, using the biosynthetic precursor levodopa or other drugs that activate dopamine receptors [27, 28]. These therapies are often successful for some time in alleviating the abnormal movements, but most patients eventually develop motor complications as a result of these treatments [29, 30]. These complications include wearing off, the abrupt loss of efficacy at the end of each dosing interval, and dyskinesias, involuntary and sometimes violent writhing movements. Wearing off and dyskinesias produce substantial disability, and frequently prevent effective therapy of the disease [31, 33].

Currently available tools for monitoring and managing motor fluctuations are quite limited [34, 35]. In clinical practice, information about motor fluctuations is usually obtained by asking patients to recall the number of hours of ON (i.e. when medications effectively attenuate tremor) and OFF time (i.e. when medications are not effective) they have experienced in the recent past. Figure 6 shows a schematic representation of...
a motor fluctuation cycle (i.e. interval between two medication intakes) and the occurrence of dyskinesia. Dyskinetic movements are observed at certain points of the cycle. Patients are asked to report the duration of these symptoms in terms of percent of awake time spent in each state. This retrospective approach is formalized in Subscale Four of the Unified Parkinson’s Disease Rating Scale (UPDRS) [36] referred to as “Complications of Treatment”. This kind of self-report is subject to both perceptual bias (e.g. patients often have difficulty distinguishing dyskinesia from other symptoms) and recall bias. Another approach is the use of patient diaries, which does improve reliability by recording symptoms as they occur, but does not capture many of the features that are useful in clinical decision-making [37]. In clinical trials of new therapies, both the diary-based approach [37] as well as extended direct observations of the patients in a clinical care setting [38] have been used, but both capture only a small portion of the patient’s daily experience and are burdensome for the subjects.

Based on these considerations, our team [39] and others [40] have developed methods that rely on wearable technology to monitor longitudinal changes in the severity of symptoms and motor complications in patients with Parkinson’s disease. In our own study, we recruited twelve individuals, ranging in age from 46 to 75 years, with a diagnosis of idiopathic Parkinson’s disease (Hoehn & Yahr stage 2.5 to 3, i.e. mild to moderate bilateral disease) [36]. Subjects delayed their first medication intake in the morning so that they could be tested in a “practically-defined OFF” state (baseline trial). This approach is used clinically to observe patients during their most severe motor symptoms. Subjects were instructed to perform a series of standardized motor tasks utilized in clinically evaluating patients with Parkinson’s disease. Accelerometer sensors positioned on the upper and lower extremities were used to gather movement data during performance of the standardized series of motor tasks mentioned above. The study focused on predicting tremor, bradykinesia, and dyskinesia based on features derived from accelerometer data. Raw accelerometer data were high-pass filtered with a cutoff frequency of 1 Hz to remove gross changes in the orientation of body segments [41]. An additional filter with appropriate characteristics was applied to isolate the frequency components of interest for estimating each symptom or motor complication. Specifically, the time series were band-pass filtered with bandwidth 3-8 Hz for the analysis of tremor, and they were low-pass filtered with a cut-off frequency of 3 Hz for the analysis of bradykinesia and dyskinesia. All the filters were implemented as IIR filters based on an elliptic design. The accelerometer time series were segmented using a rectangular window randomly positioned throughout the recordings performed during performance of each motor task. [42] Features were extracted from 30 such data segments (i.e. epochs) for each motor task from the recordings performed from each subject during each trial. Five different types of features were estimated from accelerometer data recorded from different body segments. The features were chosen to represent characteristics such as intensity, modulation, rate, periodicity, and coordination of movement. We implemented Support Vector Machines to predict clinical scores of the severity of Parkinsonian symptoms and motor complications. Our results demonstrated that an average prediction error not exceeding a few percentage points can be achieved in the prediction of Parkinsonian symptoms and motor complications from wearable sensor data. Specifically, average prediction error values were 3.5 % for tremor, 5.1 % for bradykinesia, and 1.9 % for dyskinesia. [43].
4. Assessment of Rehabilitation Interventions in Patients Post Stroke

More than 700,000 people are affected by stroke each year in the United States [44]. Strokes affect a person’s cognitive, language, perceptual, sensory, and motor abilities [45]. More than 1,100,000 Americans have reported difficulties with functional limitations following stroke [46]. Recovery from stroke is a long process that continues beyond the hospital stay and into the home setting. The rehabilitation process is guided by clinical assessments of motor abilities, which are expected to improve over time in response to rehabilitation interventions. Telerehabilitation has the potential to facilitate extending therapy and assessment capabilities beyond what can be achieved in a clinical setting.

Accurate assessment of motor abilities is important in selecting the best therapies for stroke survivors. These assessments are based on observations of subjects’ motor behavior using standardized clinical rating scales. Wearable sensors could be used to provide accurate measures of motor abilities in the home and community settings and could be leveraged upon to facilitate the implementation of telerehabilitation protocols. Our team has performed pilot studies exploring the use of wearable sensors (accelerometers) and an e-textile glove-based system (herein referred to as “data glove”) designed to monitor movement and facilitate the implementation of physical therapy based on the use of video games.

We demonstrated that accelerometers can be utilized to predict the Wolf Functional Ability Score (FAS). The Wolf FAS provides a measure of the subject’s quality of movement based on an evaluation of the quality of movement during performance of the Wolf Motor Performance Test [47]. The scores capture factors such as smoothness, speed, ease of movement, and amplitude of the compensatory movements. Twenty-three subjects who had a stroke within the previous 2 to 24 months were recruited for the study. Accelerometers were positioned on the sternum and the affected (i.e. hemiparetic) arm. Subjects performed multiple repetitions of tasks requiring reaching and prehension, selected from the Wolf Motor Performance Test. The tasks included reaching to close and distant objects, placing the hand or forearm from lap to a table, pushing and pulling a weight across a table, drinking from a beverage can, lifting a pencil, flipping a card, and turning a key. Accelerometer data were processed to derive features that captured different aspects of the movement patterns and were fed to a classifier built using a Random Forest. The Random Forest approach is based on an ensemble of decision trees and is suitable for datasets with low...
feature-to-instance ratio. We assessed the reliability of the estimates achieved using this method by deriving the prediction error for each of the investigated motor tasks. The estimated prediction error for such motor tasks ranged between about 1% and 13%. This is a very encouraging result as it suggests that FAS scores could be estimated via monitoring motor tasks performed by patients in the home and community settings using accelerometers.

Our team also studied the feasibility of utilizing a sensorized glove to implement physical therapy protocols for motor retraining based on the use of video games. The glove was utilized to implement grasp and release of objects in the video games. This function was achieved by defining a measure of “hand aperture” and estimating it based on processing data gathered from the data glove. Calibration of the data glove was achieved by asking individuals to hold a wooden cone-shaped object with diameter ranging from 1 cm to 11.8 cm at different points of the cone corresponding to a known diameter. The output of the sensors on the glove was used to estimate the diameter of the section of the cone-shaped object corresponding to the position of the middle finger. A linear regression model was utilized to estimate the above-defined measure of “hand aperture” (dependent variable) using the glove sensor outputs as independent variables. Encouraging results were achieved from the study. The estimation error that marked the measures of “hand aperture” as defined above was smaller than 1.5 cm. We consider this result as satisfactory in the context of the application of interest, i.e. the implementation of video games to train grasp and release functions in individuals post stroke.

Overall, the results herein summarized indicate that the investigated wearable technologies are suitable to implement telerehabilitation protocols.

Figure 7. A subject testing the data glove herein described in combination with a robotic system for rehabilitation.
5. Conclusions

The assessment of the impact of rehabilitation interventions on the daily life of individuals is essential for developing protocols that maximize the impact of rehabilitation on the quality of life of individuals. The use of questionnaires is somehow limited because questionnaires are subject to perceptual bias and recall bias. Furthermore, relying on questionnaires is bound to introduce a delay in the response to changes in patient’s status since the information needed to make a clinical decision concerning changes in rehabilitation interventions is not readily available on a continuous basis but rather questionnaires are administered sporadically. Wearable technology has the potential to overcome limitations of existing methodologies to assess the impact of rehabilitation interventions on the real life of individuals. Miniature unobtrusive sensors can provide clinicians with quantitative measures of subjects’ status in the home and community settings thus facilitating making clinical decisions concerning the adequacy of ongoing interventions and possibly allowing prompt modification of the rehabilitation strategy if needed. In this chapter, we presented three applications that point at potential areas of use of wearable technology in rehabilitation.

In the first example, we showed that wearable sensors can provide clinicians with a tool to monitor exercise compliance in patients with COPD. We also showed that activities of daily living that are associated with different systemic responses can be identified with high reliability. It is conceivable that based on trends identified via analysis of changes in activity level and systemic responses associated with certain motor tasks, we could achieve early detection of exacerbation episodes. The impact on our ability to care for patients with COPD would be paramount.

In the second example, we demonstrated that we can monitor the severity of symptoms and motor complications in patients with Parkinson’s disease. This is important in the late stages of the disease when motor fluctuations develop. Since motor fluctuations span an interval of several hours, observations performed in a clinical setting (typically limited to the duration of the outpatient visit, i.e. about 20-25 minutes) are not sufficient to capture the severity of motor fluctuations. Monitoring patients in the home and community settings could therefore substantially improve the clinical management of patients with late stage Parkinson’s disease. Our results suggest that the technique summarized in this chapter could be extended to monitoring patients with other neurodegenerative conditions that are accompanied by motor symptoms.

Finally, we demonstrated that wearable technology could provide clinicians with a means to assess functional ability in individuals post stroke. This is important because we currently have very limited tools to assess the impact of rehabilitation interventions on the real life of patients. Although it is expected that therapeutic interventions that are associated with improvements in impairment level and functional level lead to an improved quality of life, it would be very useful to quantify such impact and compare different interventions measuring their impact on the performance of activities of daily living via processing data gathered in the home and community settings. Tools to monitor patients in the home and community settings could lead to new criteria for adjusting interventions that maximize the impact on real life conditions of the adopted therapeutic intervention. We anticipate that such criteria would allow clinicians to help patients achieving higher level of independence and better quality of life.

All in all, the examples provided in this chapter indicate that wearable technology has tremendous potential to allow clinicians to improve quality of care thus resulting in
a likely improvement in quality of life in individuals in response to rehabilitation. The next challenge in wearable technology is indeed to demonstrate that such methodologies can have a significant impact on the quality of care provided to patients and their quality of life.

Acknowledgments

The author wishes to thank Dr. Sunderasan Jayaraman, Dr. Alex (Sandy) Pentland, and Dr. William Tang for allowing him to utilize figures that they utilized in previous communications and for their input on a draft of this chapter. The work on wireless technology summarized in this chapter was largely carried out by Dr. Matt Welsh and his team at the Harvard School of Engineering and Applied Sciences. Applications of e-textile solutions were pursued jointly with Dr. Danilo De Rossi, University of Pisa, and his associates Dr. Alessandro Tognetti and Mr. Fabrizio Cutolo. Dr. Rita Paradiso (Smartex) provided expertise and support in the development of the data glove discussed in this chapter. The pilot study concerning the application of wearable technology to monitor patients with COPD was performed with Dr. Marilyn Moy at Harvard Medical School and Ms. Sherrill Delsey, currently at the MIT Lincoln Laboratory, who was at Spaulding Rehabilitation Hospital at the time the study described in this chapter was performed. The development of methodologies to assess the severity of symptoms and motor complications in patients with Parkinson’s disease was performed with Dr. John Growdon and Ms. Nancy Huggins at Massachusetts General Hospital. Algorithms for the analysis of accelerometer data were developed by Mr. Shyamal Patel, Northeastern University. Mr. Richard Hughes, currently with Partners HomeCare, who was at Spaulding Rehabilitation Hospital at the time the study described in this chapter was performed, provided clinical scores for all the patients’ recordings. Mr. Richard Hughes also contributed to the pilot study we performed to assess the use of wearable technology in patients post stroke. Medical expertise for this project was provided by Dr. Joel Stein, currently at Columbia University, who was at Spaulding Rehabilitation Hospital at the time the study was performed. Algorithms for the analysis of data recorded from patients post stroke were developed by Mr. Todd Hester, currently at University of Texas Austin, who was at Spaulding Rehabilitation Hospital at the time the study was performed. Mr. Shyamal Patel, Northeastern University, also contributed to the development of these algorithms.

References


