Continuous Assessment of Gait Velocity in Parkinson's Disease from Unobtrusive Measurements

Misha Pavel, *Member, IEEE*, Tamara Hayes, *Member, IEEE*, Ishan Tsay,
Deniz Erdogmus, *Member, IEEE,* Anindya Paul, *Member, IEEE*,
Nicole Larimer, Holly Jimison, *Member, IEEE,* John Nutt

Abstract— **The ability to assess the neurological state of patients with neurodegenerative diseases on a continuous basis is an important component of future care for these chronically ill patients. In this paper we describe a set of algorithms to infer gait velocity and its variability using data from an unobtrusive sensor network by incorporating a simple dynamic description of a patient's movements within his or her residence. The sensors include a combination of passive motion detectors and active radio frequency identification tags. The dynamic model is a simple 4 state hidden Markov model. We investigated the ability of this model to assess gait velocity and its variability using data from a six month pilot study of several patients with early stage Parkinson's disease.**

I. Introduction

THE ability to assess the sensory, motor and cognitive functionality of an individual is an important problem in caring for individuals with chronic diseases, as well as for the healthy elders. Current methods relying on observations, e.g., Unified Parkinson's Disease Rating Scale (UPDRS), Clinical Dementia Rating (CDR) as well as those relying on neuropsychological testing are inherently highly variable, costly, and to some extent depend on the testers' capabilities and training. As such, they are administered infrequently, require multiple administrations to assess long-term change, and are generally difficult to use to assess the instantaneous state of the patient.

Yet, in many situations it would be desirable to assess the functions related to the neurological state of the patient on a continuous basis. For example, in the care of patients with Parkinson's disease (PD), the instantaneous aspects of gait velocity may be a useful measure for the determination of the administration of drugs, such as Levodopa. Also, continuous measurement of motor function would be a large improvement over current techniques of estimating impact of symptomatic therapies on motor function throughout the day using diaries filled out by study subjects. Further, continuous longitudinal measurements would be mare accurate way to estimate the effects of treatments that are hypothesized to alter the progression of a motor disorder.

Our approach to the problem of assessment is based on a combination of neural informatics and sensor technology. Neural Informatics is a collection of computer-based methods that address issues at the intersection of neural engineering, neuroscience and clinical practice. The methods include modeling clinically relevant aspects of neurological states of both individuals and populations. In our preliminary studies as well as those from other laboratories, the variability of the various metrics appears to be as important as the average values. For example, variability in mobility measures, such as gait velocity or stride length, have been shown to correlate with age, and with dementias, such as those associated with Alzheimer's Disease [1]. Motor pattern generating mechanisms and gait velocity appear to be useful predictors of future cognitive decline [2, 3]. The goal of our approach is to replace the occasional sampling of cognitive and motor function using clinic-based control tests with continuous observations in the patients' natural environments. A system that can assess aspects of mobility on a continuous basis can, of course, be used to assess the variability of these measures.

In this paper, we describe an approach to the unobtrusive measurement of gait velocity and its variability based on continuous monitoring of the PD patients in their homes. In particular we extend our prior work [6] by incorporating a simple dynamic model of the movements of the individuals in their dwellings.

II. Unobtrusive measurement of Gait Velocity

The system for the unobtrusive measurement of gait comprises two components that will be described in the following two sections: A) a sensor system for sensing and collecting the raw data, and B) a set of algorithms that estimate the parameters of interests from the raw data.

A. Sensor System

One of the most important requirements of the sensor and assessment system is its unobtrusive or minimally intrusive nature [6] as well as its economical feasibility. In order to develop a system that is minimally intrusive, we have been

This work was supported in part by grants from NIH, NSF, and the Kinetics Foundations to Oregon Health and Science University.

M. Pavel is in Biomedical Engineering and Medical Informatics at Oregon Health and Science University (OHSU) Tamara Hayes is Assistant Professor in Biomedical Engineering at OHSU,

Deniz Erdogmus is Assistant Professor in Biomedical Engineering and Computer Science and Electrical Engineering at OHSU

Ann Tsay is Research Associate in Biomedical Engineering at OHSU,

Nicole Larimer Research Assistant in Biomedical Engineering at OHSU,

Holly Jimison is Associate Professor in Medical Informatics and Biomedical Engineering at OHSU

John Nutt is a Professor in Neurology at OHSU.

investigating approaches that would be affordable by a large number of patients and their families. For example, we have been investigating systems based on passive infrared sensors (PIR) and contact switches that would be deployed in a similar manner as are the components used in many security systems.

The general architecture installed in a typical home is shown in Fig. 1. When a sensor detects the presence of a moving human body at the normal body temperature and the motion signal exceeds a fixed threshold, it fires. There are various details that control the firing, such as the refractory period of the sensor following a firing, but a discussion of these is beyond the scope of this paper. In general, the inference of the gait velocity is based on the time that it takes to traverse from one part of the patient's home to another – this approach, in conjunction with semi-Markov models was described previously in an article by Pavel et al. in 2006 [7].

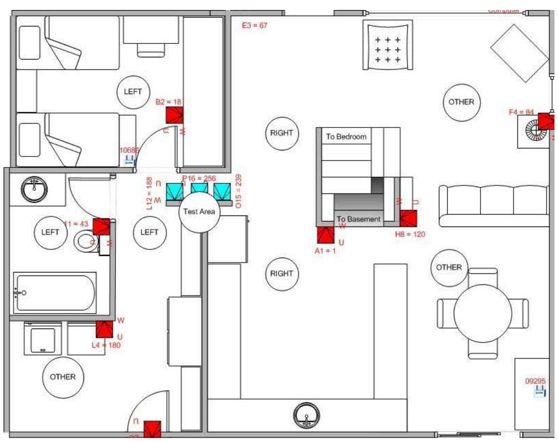

Fig. 1. Example of a part of a residence with a number of PIR sensors, RFID receiver stations and the test area.

In some dwellings it is possible to make the measurements of speed of walking more directly by taking advantage of the layout. In particular, if the residence has a hall or a corridor, we would place three modified PIR detectors the hall in a row as shown in Fig. 1. The PIR motion detectors placed in the "*test area*", i.e., the hall, were modified to restrict their field of view to 4^o. The PIR monitoring system is using a simple wireless communication network in order to collect the data. The main data relevant to monitoring mobility consist of records of PIR motion detectors firing events.

In dwellings with multiple residents, it is necessary to identify the particular individual associated with different events recorded from the PIR motion detectors. In this study, we used a commercially available RFID location tracking system for this purpose (HomeFree, Inc). Each individual residing in the same residence wore a small RFID device in the form of a watch that emits periodically – every 4 seconds – a signal received by three or more base stations.

B. Inference Algorithms

The unobtrusive nature of the sensor system is inherently plagued with considerable uncertainties arising from the fact that the measured phenomenon, e.g. gait velocity is only indirectly related to the sensed data. In order to compensate for this, we base our inference on a fusion of information from a set of passive infrared detectors, contact switches and active radio frequency identification (RFID) system.

As noted above, the incorporation of the RFID system is essential for inference in dwellings with multiple residents. Such was the case in a recent pilot study of a small number of patients with Parkinson's disease and their spouses that served as control subjects.

The measurement of speed of walking in the test area is a trivial problem whenever an observation consists of the three detectors firing in one of two temporal orders consistent with a particular direction of the movement. In those cases, the time between the first and the third detector events is taken as the time to walk the distance between detectors. The difficult problem is to infer the identity of the walking individual.

Our original notion was that the received signal strength indicator (RSSI) would provide sufficient information to determine the locations of each individual. However, this was not possible due to the variability of the RSSI signal and its lack of monotonicity with the distance. In our prior work [6], this problem was addressed by static modeling of the RSSI distribution over the dwelling, and the use of the expectation-maximization (EM) algorithm to best estimate the individual associated with the motion detector events [9,10]. Despite its fairly successful deployment, further improvements could be achieved by adding constraints due to the sequential dependencies – dynamics – of the moving individuals.

The general approach is to determine the likelihood of each individual resident being in the test area – a similar approach to [6] – combined with a dynamic model based on the assumption that the movements of an individual could be described by a simple hidden Markov model (HMM) shown in Fig. 2.

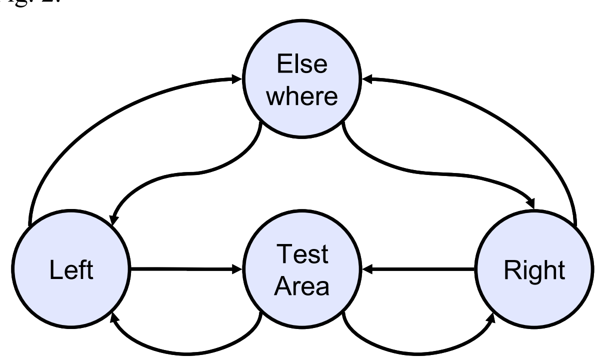

Fig. 2 Hidden Markov model representing the dynamics of the patient in his residence.

In particular, the HMM developed for the inference was assumed to consist of 4 unobservable states described by

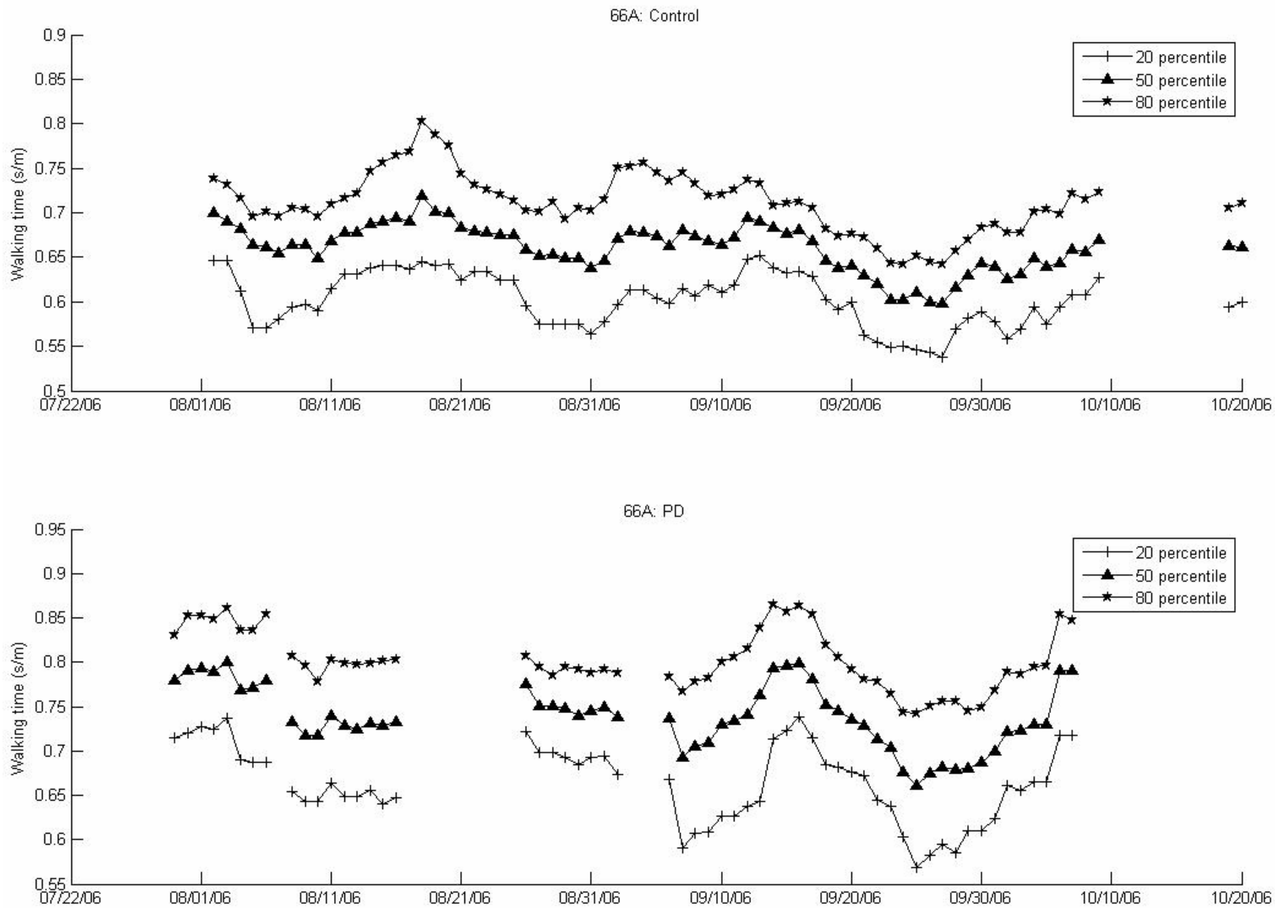

Fig. 3. Example of results from one house with a Parkinson's patient (lower graph) and a control subject (upper graph). The abscissa is the date of each observation and the ordinate is the time it takes to walk along the test area. The three different sets of data correspond to the 20, 50, and 80 percentiles of walking times. The missing data indicate that the corresponding individual was not in the residence. The data are computed using 7 day moving

locations in relation to the test area, namely:

1. Left of the test area
2. Right of test area
3. At the test area
4. Other – Elsewhere

The transition probabilities p_{jk} between each pair of states are constrained by the direction of the patient's movement as sensed by the PIR motion detector sequences – left to right and vice versa and the general topology of the HMM is shown in Fig. 2. The transition probabilities were determined using the occupancy of the different parts of the dwelling assessed by the cumulative number of motion detector events in each part of the house. Table 1 lists an example of the transition probabilities used in conjunction with the house diagram shown in Fig. 1.

TABLE 1
EXAMPLE OF TRANSITION PROBABILITIES

	Left	Test	Right	Other
Left	0.20	0.60	0.00	0.20
Test	0.30	0.20	0.50	0.00
Right	0.00	0.33	0.33	0.33
Other	0.25	0.00	0.25	0.50

The notation to describe the inference algorithm is similar to that used in [6]. The observable outputs, R in each state are vectors of the RSSI values recorded by each receiver or base station in the residence. The probability density of the observable RSSI are given by $f_i\left(R \mid q\right)$, where q is the state in the HMM and i is the individual. These probability density functions were estimated using a Gaussian mixture model (GMM) with parameters estimated using the expectation-maximization approach, from calibration data gathered during the initial installation of the sensor system. The calibration RSSI data were obtained by collecting RSSI data from each "significant" location in the patient's dwelling, as identified by the patient or the spouse. For the purpose of this study, each resident is associated with a particular HMM and these individual HMMs are treated as statistically independent.

III. RESULTS

The data collected in the pilot study from 6 houses were used to examine the applicability of this approach. In this presentation we illustrate the approach on the data from one of the houses. The data from the patients' dwellings were processed whereby the events form the motion detectors in the test area were used to identify all the instances when the three detectors fired in one of the temporal orders corresponding to rightward or leftward motion (ignoring partial sequences). For each time *t* associated with the first detector event, the sequence of RSSI samples was used

$$\mathbf{R} = \{R(t-3\Delta), R(t-2\Delta), R(t-\Delta),$$
$$R(t), R(t+\Delta), R(t+2\Delta), R(t+3\Delta)\}$$

to determine the most likely sequence of states consistent with the observed RSSI. The likelihood of any particular sequence of states $\mathbf{Q}_i = \{q_1, q_2, \dots q_7\}$, for the *i*-th individual is given by

$$\lambda_i(\mathbf{R}) = \Pr\{\mathbf{R} \mid \mathbf{Q}_i\}$$
$$= \pi_{q_1} f_i(R_{t-3} \mid q_1) \prod_{k=1}^{6} p_{k,k+1} f_i\left(R_{t+\Delta(k-3)} \mid q_{k=1}\right),$$

where π_q is the prior probability of the state q_1 and $p_{k,k+1}$ is the transition probability from state k to state k+1. Using Viterbi search, the inference algorithm found, for each individual, the most likely sequence of states $\mathbf{Q}_i^*$ given the RSSI observations. Since the identity of the walking individual is not known with certainty, the overall distribution $g(t)$ of the observed times to walk is a mixture of the distributions associated with each individual,

$$g(t) = \sum_{i=1}^{N} \alpha_i g_i(t),$$

where α_i is the probability that the observation is associated with the *i*-th individual. Conversely, given the probability that a particular measurement is associated with the *i*-th individual, it is possible to estimate the expected value and the variance of the time to walk distribution for that individual using the probabilities derived from the HMM. In particular, using a Bayesian estimation procedure with uniform priors, the estimate of the expected value for the time to walk for the *i*-th individual is given by:

$$E[T_i] = \sum_t w_i(\mathbf{R}_t) T_{i,t}$$

Where $T_{i,t}$ is the walking time measurement, w_i is a weight determined as follows: w_i is zero if $\mathbf{Q}_i^*$ does not contain q_{test} and

$$w_i = \frac{\lambda_i(\mathbf{R}_t)}{\sum_j \lambda_j(\mathbf{R}_t)}$$

for all sequences that contain the state q_{test}, corresponding to the test area. In other words, the weight is determined by the relative likelihood of each individual walking in the test area.

An example of the results from one house occupied by a Parkinson's patient and his spouse is shown in Fig. 3. The distribution of walking times for the *i*-th individual was computed using the probability estimates that a given measurement came from the i-th individual. The triangles correspond to the median estimates. The data indicate higher variability of the walking times of the Parkinson's patient..

IV. Conclusion

We have developed a technique to reduce the uncertainty associated with unobtrusive measurement of mobility with multiple individuals in a single dwelling. We have demonstrated that a simple 4 state HMM with minimal training can incorporate the dynamic aspects of the sequential data. Although the application of this approach to the data from our pilot study appears to be promising, the real evaluation of this approach would require a data set with known ground truth. Alternatively, there are additional enhancements of this approach that would improve the inference; for example, including a coupling between the HMMs corresponding to each individual would impose additional constraints and probably improve the inference.

Acknowledgment

We thank Jeff Kaye for his leadership in the development of related approaches in the monitoring of elders and John Hunt for his engineering and technical expertise and advice.

References

[1] P. L. Sheridan, J. Solomont, N. Kowall, and J. M. Hausdorff, "Influence of executive function on locomotor function: divided attention increases gait variability in Alzheimer's disease," J Am Geriatr Soc, vol. 51, pp. 1633-7, 2003.

[2] R. Camicioli, D. Howieson, B. Oken, G. Sexton, and J. Kaye, "Motor slowing precedes cognitive impairment in the oldest old," Neurology, vol. 50, pp. 1496-8, 1998.

[3] R. Camicioli, M. M. Moore, G. Sexton, D. B. Howieson, and J. A. Kaye, "Age-related brain changes associated with motor function in healthy older people," *J Am Geriatr Soc*, vol. 47, pp. 330-4, 1999

[4] T. L. Hayes, M. Pavel, and J. A. Kaye, "An unobtrusive in-home monitoring system for detection of key motor changes preceding cognitive decline," presented at 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Francisco, CA, 2004.

[5] T. Hayes, M. Pavel, P. K. Schallau, and A. M. Adami, "Unobtrusive monitoring of health status in an aging population.," presented at 5th International Conference on Ubiquitous Computing, Seattle, Washington., 2003.

[6] T.L. Hayes, M. Pavel, A. Adami, N. Larimer, A. Tsay and J. Nut, "Distributed healthcare: Simultaneous assessment of multiple individuals, Pervasive Computing", 6 (1), 36-43, 2007.

[7] M. Pavel, T. L. Hayes, A. Adami, H. B. Jimison, and J. Kaye, "Unobtrusive assessment of mobility," presented at 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, New York, NY, 2006.

[8] R. B. Postuma, , T. Arenovich, A. E. Lang, Does severity of Parkinson's disease vary according to season? Movement Disorders, Volume 20, Issue 4 ,2004,pp 476 – 479

[9] A. Dempster, N. Laird, and D. Rubin, "Maximum likelihood from incomplete data via the EM algorithm," *Journal of the Royal Statistical Society*, vol. 39, pp. 1-39, 1977.

[10] M. Jordan and R. Jacobs, "Hierarchical mixtures of experts and EM algorithm," *Neural Computation*, vol. 5, pp. 181-214, 1994.