Proceedings of the 28th IEEE
EMBS Annual International Conference
New York City, USA, Aug 30-Sept 3, 2006

Unobtrusive Assessment of Mobility

Misha Pavel, *Member, IEEE*, Tamara L. Hayes, *Member,* Andre Adami, *IEEE*, Holly Jimison, *Member, IEEE*,
Jeffrey Kaye, *Member, IEEE*

Abstract—**This paper describes a model-based approach to the unobtrusive monitoring of elders in their home environment to assess their health, daily activities, and cognitive function. We present a semi-Markov model representation with automated learning to characterize individual elder's mobility in the home environment. The assessed mobility can be used to characterize the elder's speed of walking and can serve as one of the predictors of future cognitive functionality and the ability of elders to live independently in their home environment.**

I. Introduction

THE demographics of our society are rapidly shifting toward an aging population with concomitant increases in chronic diseases and disabilities. People aged 65 and older are the fastest growing segment of the US population. By 2030 over 4 million Americans will be over age 85 [1]. This shift has been accompanied by rising health care costs, creating both a social and economic burden of crisis proportions. Providing high-quality, cost-effective health care for the elderly has become a high priority issue for most governments. Approximately 20% of people 85 and over have a limited capacity for independent living [2] and require daily home care.

The impact to elders' families and to our society of providing this care includes loss of wages for family caregivers [3], a reduction of an experienced workforce, the financial cost of health care itself, and a reduced quality of life for both the elderly and their family caregivers. Our approach to improving elder care has been to develop unobtrusive home monitoring techniques to enhance elder independence and to provide activity summary information to remote caregivers (both family and professional). Our initial work is focused on the early detection of reduced physical and cognitive function, to allow intervention before problems arise.

The work described in this paper is based on an approach to the unobtrusive home monitoring of elders using motion and contact sensors to determine location, speed of walking and daily activities to detect early changes in cognitive function. The main purpose of this paper is to illustrate the issues and approaches involved in the deployment of unobtrusive monitoring in support of a home care application.

This work was supported in part by a grant from NIA P30 AG024978 and by a grant form Intel Corporation entitled "Intelligent systems for the early detection of dementia".

M. Pavel, Ph.D., T.L. Hayes, Ph.D., and A. G. Adami, Ph.D. are with the Biomedical Engineering Department at Oregon Health & Science University, Portland, OR 97239 (e-mail: pavelm@ohsu.edu; hayest@bme.ogi.edu, aadami@bme.ogi.edu)

H.B. Jimison, PhD., is with the Department of Medical Informatics and Clinical Epidemiology at Oregon Health & Science University, Portland, OR 97239 (e-mail: jimisonh@ohsu.edu)

J.A. Kaye, MD, is with the Department of Neurology at Oregon Health & Science University, Portland, OR 97239 (e-mail: kaye@ohsu.edu)

II. Unobtrusive Monitoring of Mobility

A number of researchers as well as commercial organizations have begun to explore various methods for remote monitoring of the activity of people in their homes Some of these studies have demonstrated the feasibility of remotely monitoring activities in the home[4,5,6]. Although there are many aspects of elders' daily activities that could be assessed, monitoring of mobility and speed of walking appears to be particularly useful for several reasons.

First, mobility is one of the key capabilities that is required for elders to perform many of the activities of daily living and therefore to maintain independence. Second, the ability to move safely is likely to be related to the propensity of falls and their costly consequences. Third and the most relevant to the present work is that aspects of mobility such as speed of walking are potential predictors of future cognitive function. In particular, the results of a longitudinal study at the Oregon Health and Science University suggested that reduced performance on simple tests of motor function precedes and may be predictive of future cognitive decline [7].

The results of the longitudinal study were based on periodic tests performed in the clinic on the average every six months. This approach to assessment is inconvenient to the elders, very labor intensive and therefore expensive. In addition, the infrequently sampled measurements are plagued with variability and biases. Such approaches are, therefore, not appropriate in the routine care for the elders.

With the advancements in technology, researchers have attempted to deploy various techniques for continuous assessment of mobility with various degree of obtrusiveness. Among the least obtrusive techniques are those based on accelerometers attached to limbs. The accelerometer-based devices, commonly called actigraphs, have been used to measure physical activity of a variety of patients. Although actigraphs sense acceleration, the raw acceleration data are integrated over set time intervals and the recorded output is usually a measure of the magnitude of the average acceleration. Although the actigraphy results have been shown to correspond to some aspects of mobility [8], the results confound mobility with other small movements of the limbs and the body. Other techniques that may provide more direct measures of mobility, such as video cameras, are considered to be too obtrusive to be used except in special circumstances.

In this paper we examine an approach to the assessment of mobility based on the deployment of inexpensive technology based on passive infrared (PIR) detectors, similar to those used for security systems. These detectors are designed to detect certain dynamic patterns of infrared energy within their field of view. The objective of the PIR design is to detect movements of human body. Accordingly, the desirable features of these detectors include unobtrusiveness of the sensing, low cost, low power consumption, and negligible maintenance. The low power consumption is achieved by having the detectors respond to onset of motion, followed by infrequent sampling. Each discrete response of each detector is transmitted via low power radio frequency radio to the base station. Despite their features, these detectors have serious shortcomings. The most serious limitation of these detectors is that their output is related only indirectly to the clinically relevant aspects of mobility such as the speed of walking.

To overcome this serious shortcoming, we have used a combination of approaches such as modifying the sensors' field of view, designing a careful sensor placement and developing statistical pattern recognition algorithms and corresponding models for estimating speed of walking.

In this paper we describe an approach based on dynamic models that enable us to fuse information from multiple sensors and support statistical inference of clinically relevant aspects of mobility from the suite of sensors.

III. Model-Based Inference

A. Theoretical Framework: Modeling Mobility

Mobility can be interpreted in a variety of ways, depending on the level of analysis. At the lowest levels, mobility can be defined by the instantaneous speed of motion and by the path of motion in an appropriate coordinate space. For example, for a continuous state space representation, with an instantaneous location $\vec{x}(t)$

$$\vec{x}(t+\Delta t)=\vec{x}(t)+\vec{v}(t)\Delta t. \quad (1)$$

At a slightly higher level, mobility can be defined in terms of transition from one discrete location to another. At the highest level mobility can be viewed as an abstract ability, an important component of many activities of daily living.

The data to be used to make the assessment are responses transmitted from the motion sensors. In particular, the observations, i.e., output of the sensors, can be represented in terms of a vector,

$$\vec{s}(t)=\{s_1(t),s_2(t),\ldots,s_n(t)\} \quad (2)$$

where each subscript denotes a particular sensor event. The entire set of observations is then denoted by $\mathbf{S}$.

Depending on the architectural constraints, it may be possible to measure speed of walking, i.e., $\left|\vec{v}(t)\right|$ by strategically placing several motion detectors along the walls of a hallway or a corridor [9] This placement of the detectors enabled us to measure the speed of walking in a relatively direct manner.

In the majority of residential settings, however, this approach may not be feasible. Instead, the assessment of speed will require inferences based on more indirect interpretation of the sensor data. For example, one can characterize mobility by the average time that the elder moves from one location to another within the residence. This approach requires the derivation of the elder's locations from the motion sensor data using a dynamic model with unobservable states.

B. Hidden Semi-Markov Model

There are numerous ways to estimate unobservable states of a dynamic system including various realizations of the Kalman filters, neural networks or "particle filters." The choice of the approach depends, in part, on the relationship between the states and the observable information. Due to the discrete characteristics of the observable sensor data, the framework chosen to represent the elder's movement is based on hidden semi-Markov model [11]. The difference between a Markov and semi-Markov model is that in the former the dwell time distribution in a given state is geometric and determined by the probability of return to that state, while in the latter the dwell time distribution is arbitrary. There are several ways to define semi-Markov models [9], but for the purpose of this presentation we restrict our discussion to the "segmental models" similar to those described by Ostendorf and others [12]

The HSMM is characterized by the quadruple $\Gamma=[\pi,\mathbf{A},\mathbf{B},\mathbf{\Phi}]$, where π is the prior probability of each state, $\mathbf{A}$ is the state transition probability, $\mathbf{B}$ is the observation probability of any combination of motion sensors firing for each state, and $\mathbf{\Phi}$ is the set of parameterized distributions of dwell times in each state. The basic assumption is that the transition from one state to another is independent of the prior states and is given by the transition probability matrix $\mathbf{A}$. Because of the semi-Markov property, however, the probability of a specific state at a particular point in time t is generally not independent of the prior sequence of states.

A useful interpretation the HSMM in this application is that the states represent discrete approximations of the instantaneous location of the elder. Under that interpretation each state may be associated with a discrete area within the residence and the residence is assumed to be roughly tessellated into regions $\{z_i\}$, each associated with a hidden state of the model.

The inference problem is then to estimate the sequence of

$\{z_i(t)\}$ from the sequence of sensor data defined in (2). In the HSMM framework, this amounts to finding the most likely sequence of states for a given sequence of observation. During the training phase of the HSMM, the objective is to find the set of transition probabilities and all other parameters of the HSMM to maximize the likelihood of the observed sequences.

C. Training: Estimation of Parameters

Perhaps the most critical aspect of the model is that it must be able to learn the characteristics of each particular residence as well as the idiosyncratic aspects of the behavior of each resident without manual intervention. The training must therefore be designed to work with unlabeled data. This objective is achieved by finding the parameters of the HSMM that would maximize the likelihood of the observed sequence, i.e., finding the parameter values that yield the most likely agreement between the predicted and observed sequences of states.

Since the states are not directly observable, the training is implemented by iterative techniques, in particular, the expectation-maximization (EM) algorithm, which, in the case of hidden Markov models, is also called Baum-Welch optimization [13, 14]. Because of the arbitrary nature of the dwell times in an HSMM, the complexity of the training far exceeds that of standard Markov model. The increase in complexity can be seen by decomposing the joint probability of a sequence of states, given a set of parameters Θ, into a set of products of conditional probabilities,

$$\Pr\{\mathbf{S},\mathbf{Z}\mid\Theta\} = \prod_{\tau}^{T}\Pr\{z_\tau \mid z_{\tau-1}\}\prod_{\tau}^{T}\Pr\{d_\xi \mid z_\tau, z_{\tau-1};\theta_d\}\prod_{\tau}^{T}\Pr\{s_{(\tau)} \mid z_\tau;\theta_s\} \quad (3)$$

where τ denotes a specific segment of the observation interval T, and d_ξ is the dwell time. In comparison with standard HMM models the HSMM includes the product of all possible dwell times $\prod_{\tau}^{T}\Pr\{d_\xi \mid z_\tau, z_{\tau-1};\theta_d\}$ and therefore the search for the optimal set of parameters is frequently computationally intractable.

In this application, however, the transitions occur at the time of a motion sensor firing. It is possible, therefore, to identify the segmental transitions in the "model time", and fit all the parameters of the corresponding HMM except for the dwell distributions. The dwell distributions were then determined empirically by running the HMM in real time.

As in a typical hidden Markov model, the most likely sequence of states can be computed by dynamic programming implemented in terms of the Viterbi algorithm. As in a standard HMM, the probability of a particular observation sequence $\mathbf{S}$ is computed using a forward-backward algorithm, i.e., by computing the probabilities in both forward and backward from the particular state.

Although the dwell distribution is currently determined empirically, additional simplifications can be obtained by replacing the empirical distribution by a parametric family such as such as gamma distribution. The HSMM in combination with the gamma distribution includes the classical hidden Markov model as a special case.

IV. APPLICATION AND PRELIMINARY EVALUATION

The objective of the modeling effort is to determine changes in mobility by assessing changes in the distribution of transition times between states with short dwell times. The evaluation of this approach, therefore, requires a longitudinal study which would enable a comparison between the proposed approach and the direct measurement of mobility and speed. Validating this hypothesis requires an extended longitudinal study that is beyond the scope of this paper. Instead the applicability of the model was evaluated by examining directly the likelihood of sensor data sequences, state transitions, and dwell time distributions.

The preliminary evaluation of the approach involved the installation of the PIR motion sensors in the houses of several elder subjects who lived alone. The installation comprised 12 sensors and software on the subject's computer. These sensors were MS16A, manufactured by X10 Wireless Technology. The messages from the individual sensors were received by a W800RF32A receiver (WGL & Associates) connected to the computer system via an RS232 serial line interface. The subject was monitored for several months and the data between time that the subjects got up and 12 noon were used for the analysis. The raw data were analyzed to eliminate various errors, such as collisions due to simultaneous transmission by multiple motion sensors.

	To state:				
		State 1	**State 2**	**State 3**	**State 4**
From state:	**State 1**	0	0.198	0.773	0.030
	State 2	0.017	0	0.777	0.205
	State 3	0.110	0.888	0	0.002
	State 4	0.020	0.966	0.014	0

The error correction was possible because of the redundancy in the transmission.

The next step was to determine the structure and the parameters for an HSMM that would account for the activities during the day. The training described above was performed for different number of states ranging from 3 to 10; the configuration that maximized the likelihood of the observed data with minimum number of states was selected. An example of the resulting state transitions is shown in Table 1 for one participant. By examining the observation probability matrix B, it is possible to associate the individual states with particular locations in the house as shown in Fig. 1.

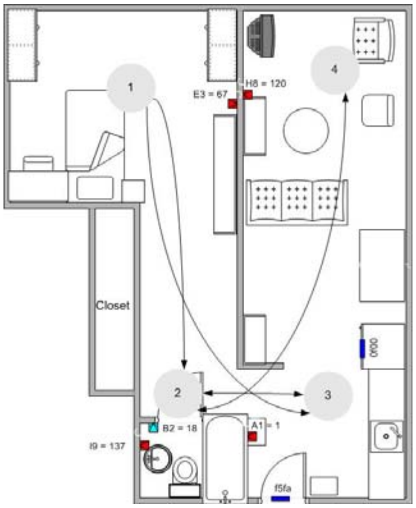

Fig. 1 Plan of the residence and the corresponding states

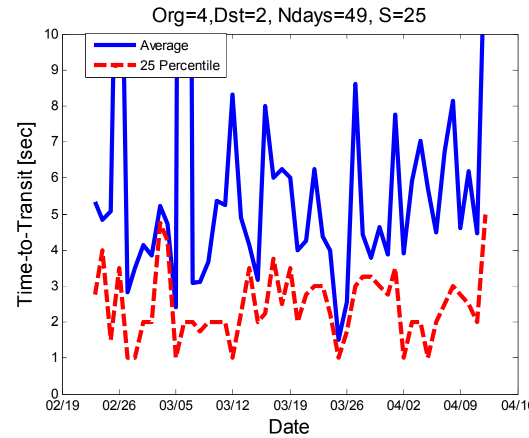

Fig. 2 Example of average (solid line) and 25th percentile of daily state transitions times.

Given these parameters, we can compute the most likely sequences of states using the observed motion sensor data and estimate transitions times for each pair of states. The underlying assumption is that the transition times can be directly related to the speed of the elder's movement within the residence and thus represent unobtrusive estimates of the speed of walking. To illustrate this concept we plot in Fig. 2 the average estimates of time to walk as well as the 25th fastest percentile, which may be more representative of the speed of movement in the absence of significant dwell time. Although the absolute speed of walking would require a calibration, relative changes can be tracked over time.

V. Conclusion

Our initial research has focused on measures of mobility with the goal of detecting deviations from normal daily activities, and consequently predicting future physical condition and cognitive performance. Despite our promising early results, these methods will require considerable future research because there are numerous issues that have not been addressed by the described system including tracking individuals in multi-occupant dwellings. Moreover, models with explicit longer term dependencies may characterize the behavior of the elders better than do Markov models.

Acknowledgment

We would like to thank Eric Dishman of Intel, and Kathy Wild of the Oregon Aging & Alzheimer's Research Center for their input on this project.

References

[1] [U. S. Census,
[2] "http://factfinder.census.gov/servlet/BasicFactsServelt?_lang=en," 2003.
[3] [P. Erickson, R. Wilson, and I. Shannon, "Years of healthy life," presented at National Center for Health Statistics, Hyattsville, MD, 1995.
[4] L. Boise, D. Morgan, J. Kaye, and R. Camicioli, "Delays in the diagnosis of dementia: Perspectives of family caregivers," *Alzheimer Disease*, vol. 14, pp. 20-26, 1999.
[5] A. P. Glascock and D. M. Kutzik, "Behavioral Telemedicine: A new approach to the continuous monitoring of activities of daily living," *Telemedicine Journal*, vol. 6, pp. 33-44, 2000.
[6] Chan, M., E. Campo, et al. (2005). "Assessment of activity of elderly people using a home monitoring system." International Journal of Rehabilitation Research **28**(1): 69-76
[7] S. Ohta, H. Nakamoto, Y. Shinagawa, and T. Tanikawa, "A health monitoring system for elderly people living alone," *Journal of Telemedicine & Telecare*, vol. 8, pp. 151-6, 2002.
[8] 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.
[9] T. L. Hayes, M. Pavel et al. , "An unobtrusive in-home monitoring system for detection of key motor changes preceding cognitive decline ," 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Francisco, CA,, 2004.
[10] M. J. Mathie, A. C. Coster, N. H. Lovell, and B. G. Celler, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," *Physiol Meas*, vol. 25, pp. R1-20, 2004.
[11] W. Feller, "On semi-markov processes," *Proc Natl Acad Sci U S A*, vol. 51, pp. 653-659, 1964.
[12] M. Ostendorf, V. Digalakis, and O. Kimball, "From HMMs to segment models: A unified view of stochastic modeling for speech recognition," *IEEE Transactions on Speech and Audio Processing*, vol. 4, pp. 360-378, 1996.
[13] L. Baum, E. T. Petrie, G. Soules, and N. Weiss, "A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains," *Ann. Math. Statist.*, vol. 41, pp. 164-171, 1970.
[14] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, pp. 257-286, 1989.