Proceedings of the 2005 IEEE
Engineering in Medicine and Biology 27th Annual Conference
Shanghai, China, September 1-4, 2005

A Methodology to Monitor the Changing Trends in Health Status of an Elderly Person by Developing a Markov Model

Alka R Kaushik, B.G.Celler, E. Ambikairajah
School of Electrical Engineering and Telecommunications, University of N.S.W, Sydney, NSW 2052, Australia
Email: alka@student.unsw.edu.au , b.celler@unsw.edu.au and ambi@ee.unsw.edu.au

Abstract - In this paper we are proposing a statistical testing methodology to monitor changing trends in the health status of elderly people. The occupancy pattern of elderly people can be modeled using a Markov chain, estimating transition probabilities of the chain and test hypotheses about them. The profile of the person for a given period can be stored as a transition matrix of a discrete, regular, ergodic Markov chain. The observation of the occupancy pattern for a given test period can be established as a test Markov chain using information from sensors such as infrared sensors, magnetic switches etc. In the absence of real time data, we have used uniformly distributed transition probabilities to define the profile of the Markov chain and then generated test Markov chain based on this model. The transition probabilities are extracted for the test and profile Markov chain using Maximum Likelihood Estimates (MLE). The statistical testing of occupancy monitoring establishes a basis for statistical inference about the system performance without generating any real time statistics for the occupancy pattern. Chi square test and likelihood ratio tests ensure that the sequences generated from the two Markov chains are statistically same. Any difference in profile Markov chain and test Markov chain could indicate a changed health status of the elderly person.

I. Introduction

Population aging is progressing rapidly in many industrialized countries. It is one of the most prominent demographic trend of this century which results in increasing the old age dependency ratio [1]. As the number of elderly people increases prevalence of disability, frailty and chronic diseases (cardiovascular, dementia, Alzheimer's disease) is expected to increase dramatically and more hospitals, nursing homes and old age homes are required to meet the demand. Population aging is a great challenge for the health care system [2].

Researchers and technologists are addressing this problem by developing technology so that older population can live healthy and longer life in their own homes and reduce the increasing cost of disease-oriented approach to care [3, 4]. One of the important measure of well being is ability to carry out day today activities such as use of kitchen & bathroom, sleeping pattern, shopping etc.. There is a direct relationship between the physical activity and health status [5]. An embedded sensor network may indicate a change in the personal routine and may detect the onset of some neurological disease [6].

In this paper, we are proposing a methodology to monitor the changing trends in health status of an elderly person living alone at home by developing a Markov model and analyzing the quantitative inferences statistically. Markov chain is used to represent quite complex physical systems, even if the number of states is not finite or the actual behavior of the system being analyzed may depend more than the present state.

The significance of Markov chain in modeling of occupancy monitoring system is twofold. Firstly, it provides a technique to model the system that can be represented with multiple transition probabilities. Secondly, it provides easy quantitative answers to the questions related to the steady state and transient behaviour of the process.

II. MODELING OF OCCUPANCY PATTERN AS A STATIONARY MARKOV CHAIN

A Markov chain model is a suitable probability model for certain random processes which have finite number of states and a finite number of equidistant time points at which observations are made. If the future state of the process depends on the present state, the chain is of first order, and the transition probabilities are same for each time interval [7]. A Markov chain is described by the initial state and the set of transition probabilities such that the conditional probability of finding the person in state X_j, given a previous state is X_i, is p_{ij}. The states are mutually exclusive, so that the elderly person can be in one and only one, state after one time index. The state transition diagram defines the possible transitions between states with the probabilities linked with each transition. As is clear from the transition diagram that all the states are communicative, the assumption of ergodicity is ensured [8]. A set of such sequences are used as test cases for the monitoring system. Real movement patterns of elderly person may be used to obtain the frequency count of each state using information from the sensors such as infrared sensors, temperature sensors etc. Markov chains with different transition probabilities represents the different parts of the day to ensure the assumption of stationarity [9] As the real usage information of each state is not available at this time, the sequences are generated stochastically based on the uniform probability distribution that represents the profile of the usage of the states. We step through each state based on the transition probability using a random number generator and simple programs. This generates a state sequence as shown in Fig.1.

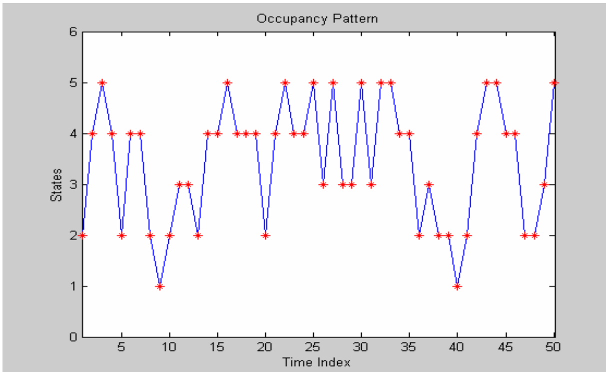

Figure 1: Profile of usage of states

In order to construct the transition diagram of discrete profile Markov chain P, state transition probabilities are estimated using maximum likelihood criterion. The construction of the transition diagram with states as indices and transition probabilities as entries for the Markov chain P requires the one step transition probability. This can be estimated from the frequency count of usage of each state. Normalizing this frequency count of each state, the following relationship estimates the stationary transition probabilities [10] of the profile Markov chain P

$$p_{ij} = N_{ij} / N_i \tag{1}$$

Where N_{ij} is number of transitions from state i to state j and N_i is all transitions from state i.

Subject to the restrictions $p_{ij} \geq 0$ and $\sum p_{ij} = 1$

The one step transition matrix obtained using (1) is shown in Fig.2

$$\begin{array}{cc} & \text{To State} \\ & \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \text{From State} \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0.4867 & 0.5133 & 0 & 0 & 0 \\ 0.2488 & 0.2495 & 0.2621 & 0.2396 & 0 \\ 0 & 0.3401 & 0.3217 & 0 & 0.3381 \\ 0 & 0.3444 & 0 & 0.3214 & 0.3342 \\ 0 & 0 & 0.3285 & 0.3405 & 0.3310 \end{bmatrix} \end{array}$$

Figure 2: One step transition probability matrix of the profile Markov chain P

The fact that the profile chain is a discrete time stationary, ergodic Markov chain allows us to perform many statistical analyses on the measurement of various probability aspects of the process such as steady state probability, mean passage time etc.[9]

III. Generation of Test Markov Chain

The profile Markov chain P with its transition probability matrix and other probability measures (stationary distribution, mean passage time etc.) is stored in the data base as the profile of the person. The transition probabilities for the profile chain are stationary. A test input sequence is a realization of the usage chain T. A series of test input sequences are generated stochastically to create a second test Markov chain T and has some minor changes in the one step transition probabilities as shown in Fig. 3.

$$\begin{array}{cc} & \text{To State} \\ & \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\ \text{From State} \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} & \begin{bmatrix} 0.5 & 0.5 & 0 & 0 & 0 \\ 0.25 & 0.25 & 0.25 & 0.25 & 0 \\ 0 & 0.33 & 0.33 & 0.33 & 0.33 \\ 0 & 0.33 & 0 & 0.33 & 0.33 \\ 0 & 0 & 0.33 & 0.33 & 0.33 \end{bmatrix} \end{array}$$

Figure 3: Transition matrix for test Markov chain T

In real time, the testing Markov chain represents the movement of a person between different states for a given period of time. The transition matrix is then extracted using maximum likelihood estimates.

IV. Statistical Analysis of Test Markov Chain

Parameter estimation and hypothesis testing are two of the major aspects of statistical testing of any mathematical model. The profile Markov chain P and test Markov chain T are ergodic stochastic sources and generate almost the same set of sequences given they have the same transition probabilities. The statistical analysis of profile Markov chain P and test Markov chain T can identify if two chains are indistinguishable within some acceptable tolerance. In order to measure this, the transition matrices of two chains is computed using maximum likelihood criterion and the hypothesis that the two transition matrices are similar is tested using $\chi 2$ goodness of fit test.

V. Hypothesis Testing Using Chi Square Goodness of Fit Test

We test the hypothesis that the observed data is a realization of profile Markov chain P.

Hypothesis H_0 = Test Markov chain T and Profile Markov Chain P is same

Alternatively H_1 = Test Markov chain T and Profile Markov Chain P is not same

$$\chi^2 = \sum_{i=0}^{m-1} \sum_{j=0}^{m-1} \frac{n_i (t_{ij} - p_{ij})^2}{p_{ij}} \tag{2}$$

Where $\sum_{j=0}^{m-1} n_{ij} = n_i$

n_{ij} = observed frequency in the (ij) cell
p_{ij} = probability of a transition from i to j in profile MC
t_{ij} = probability of a transition from i to j in test MC

The χ^2 statistics for uniform transitional probabilities of profile chain and simulated data from test chain is 17.34. The degree of freedom is calculated as the no. of cells – (the number of constraints) [11]. As the Markov chain in our example has 5 x 5 transition matrix, the degree of freedom is 20. The critical value of χ^2 at p value of 0.05 for 20 degree of freedom is 31.410. The probability level of the test is given by

$P(\chi^2 >= 17.34) = 0.6308 >> \alpha = 0.05$. Therefore, the Chi square test data does not provide sufficient data to reject H_0 at the 5 % level of significance.

If the hypothesis H_0 is rejected, it indicates that the test Markov chain T is not the realization of profile chain P, thus clearly indicating that the occupancy pattern has been changed. Additional test, however is required to further ensure a result which reliably measures the ensemble characteristics of each chain.

VI. Discriminant of Two Markov Chains

The log likelihood ratio is a fundamental computation in determining whether an observation satisfies the stated hypothesis. In this case, the hypothesis is "profile chain P is equivalent to test chain T". The expected value of log likelihood ratio (discriminant) for two arbitrary ergodic processes P and T may be computed as follows

$$D = \sum_{i,j} \pi_i p_{ij} \log_2 \frac{p_{ij}}{t_{ij}} \tag{3}$$

Where
π_i = stationary distribution of profile Markov chain
p_{ij} = probability of a transition from i to j in profile MC
t_{ij} = probability of a transition from i to j in test MC

In equation (3), discriminant D is defined only for the nonzero values of t_{ij} and is equal to zero if and only if p_{ij} is equal to t_{ij}. A discriminant value equal to zero as shown in Fig. 4 is somewhat hypothetical as it shows that the sequence properties of both chains are exactly the same. Considering the stochastic nature of the process, this is improbable but not impossible. If the value of discriminant is very small as shown in Fig. 5 the two chains are likely to generate similar sequence. When the discriminant rises above some predefined value as shown in Fig. 6, this implies that the test chain is different than the profile chain in terms of its transition probabilities and hence other analytical inferences such as steady state probability mean passage time etc. will also be different.

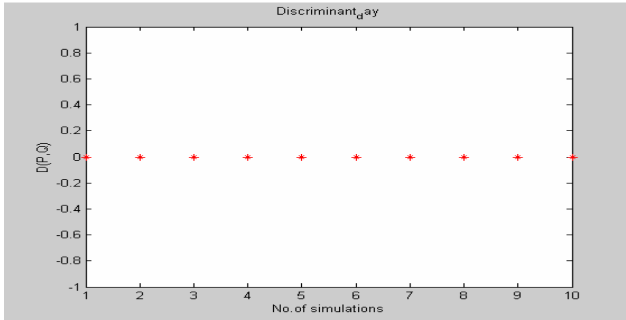

Figure 4: Discriminant for identical transition probabilities

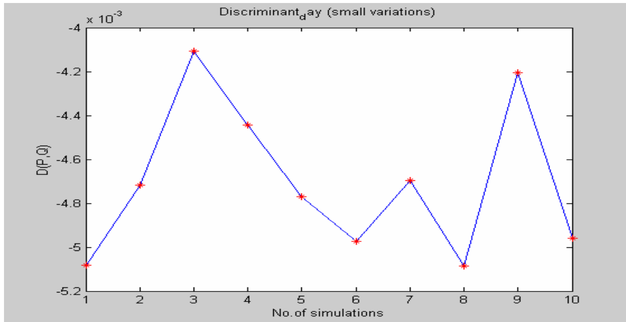

Figure 5: Discriminant for small variations in transition probabilities

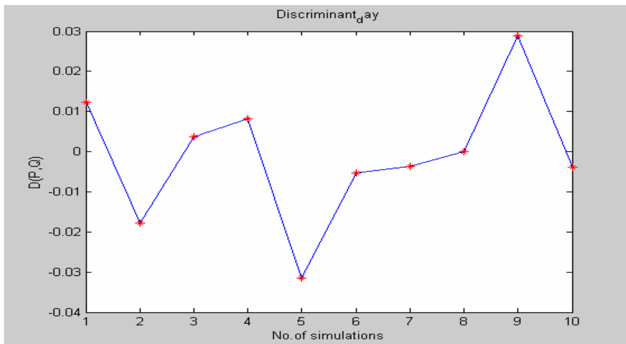

Figure 6: Discriminant for large variations in transition probabilities

If the stochastic properties of profile chain and test chain are indistinguishable within some acceptable tolerance, we assume that the health status of the elderly person is the same as before. Any statistical difference in the profile chain and the test chain may be an indicator of the deviation from the normal occupancy pattern and an alert should be generated.

VII. Conclusion

The essence of the occupancy monitoring system is to detect variations in the activities of daily living (ADL) of the elderly people living alone at home. The finite state, discrete parameter, time homogeneous Markov chain represents a theoretical framework for an unobtrusive occupancy monitoring system. The sequence of the observations that happen at a given period of time gives us the transitions between states. The transition matrix from the observation sequences is extracted using maximum likelihood estimates and may be stored in the data base server as a profile Markov chain for a given period of time. Different Markov chains represents the different parts of the day. Chi square test and discriminant analysis of the profile and test Markov chain provides ensemble characteristics of the process. Any deviation from the profile chain (with some threshold) will be considered as a deviation from the normal routine of activities. The Markov model is useful for analyzing random processes and performing statistical tests. As we are using uniformly distributed transition probabilities, the model building process helps us to establish a methodology to monitor the health status of elderly people without developing any informed statistics about their occupancy pattern. For large and complex processes the Markov model size can be very big and may have high requirements of computation time and memory. But in case of unobtrusive occupancy monitoring system the size of the model depends on the size of the house which is generally not very big for elderly people.

REFERENCES

[1] Kinsella A, Kevin, and Victoria A, *An Aging World: 2001*, in *U.S.Census Bureau, Series P95/01-1*. 2001, U.S.Government Printing Office: Washington, DC.

[2] AIHW 2002. Older Australia at a glance 2002 and Australian Institute of Health and Welfare, *Older Australia at a Glance,3rd edition*. 2002, AIHW Cat. No. AGE 25. Canberra: AIHW & Department of Health and Ageing.

[3] Dutta Roy, *Networks for Homes*. IEEE Spectrum, December 1999. **36**: p. 26-33.

[4] Jovanov, E., et al. *Prolonged Telemetric Monitoring of Heart Rate Variability Using Wireless Intelligent Sensors and a Mobile Gateway*. in *IEEE Proceedings of Joint EMBS/BMES Conference*. 2002. Houston, TX, USA.

[5] Celler BG, Lovell NH, and Chan DK, *The potential impact of home telecare on clinical practice.* The Medical Journal of Australia, 1999. **171**: p. 518-521.

[6] Korhonen, I., J. Pakka, and M.V. Gils, *Health Monitoring in the Home of Future.* IEEE Engineering in Medicine and Biology Magzine, 2003. **22**(3): p. 66-73.

[7] Kemeny John.G and Snell J. Laurie, *Finite Markov Chain*, ed. F.W. Gehring. 1976, New York: Springer-Verlag.

[8] Law, A.M. and W.D. Kelton, *Simulation Modelling and analysis*. 1991, New York: McGraw-Hill, Inc.

[9] Kaushik R Alka, Celler B.G, and Ambikairajah E. *Monitoring Health Status of Elderly People Living Alone at Home Using Markov Model (submitted)*. in *27th International Conference of the IEEE Engineering In Medicine and Biology Society (EMBS)*. 2005. Shanghai, China.

[10] Kumar P.R and Varaiya Pravin, *Stochastic Systems*. 1986: Prentice Hall, Inc.

[11] Bhat, U.N., *Elements of Applied Stochastic processes*. 1972: John Wiley & Sons, Inc.