Hidden Markov Model energy conservation approach for continuous monitoring of vital signs in geriatric care applications

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Abstract: In the recent healthcare crisis engendered by the Covid19 pandemic, wireless body area networking devices have started to play a significant role in mitigating the health problems of the elderly. The energy conservation of the device during the temporary disconnection of the sensor node can play a vital role in the broader acceptance of this technology. Here, a probabilistic hidden Markov model (HMM) is used for energy conservation, a relatively less explored area of energy conservation approach within the field of wireless sensor networks. Since the vital signs of heart rate and blood pressure are highly correlated, the heart rate and blood pressure readings are taken for model development. The classification of normal and critical data is based on the probability of observation sequences in the particular model. The hidden states are estimated using the observation sequence and the HMM parameters during disconnection. Accuracy between 0.9 and 1.0 is obtained for different series. Dynamic threshold limits are included for more adaptability of the model for varying physiological conditions of the patients. The energy conservation possible using the model is discussed. This model presents a novel approach to energy conservation using HMM, which will help continuous home monitoring of vital parameters in geriatrics.

Keywords: Hidden Markov Model, Elderly Care, Energy Conservation, Wireless Body Area Networks, Dynamic Threshold Limits.

1. Introduction

In the present busy world, people have less time to take care of older people. Even though technology cannot replace human care, it can help older people prevent many healthcare issues. Many smart home remote health monitoring devices [1] can support continuous monitoring of health parameters of an elderly patient. The recent developments in wireless body area networking technology [2] [3] have a significant role in advancing the continuous monitoring of healthcare devices. Energy conservation of sensor node is an essential parameter for the acceptance of such devices by the patients. Even though different energy conservation approaches [4][5] had already been introduced in wireless sensor networks [6], the energy conservation using probabilistic prediction approaches are comparatively less explored.

Continuous monitoring of vital signs can play a crucial role in preventing cardiovascular risks in elderly patients. Suppose we consider the temporary disconnection of the sensor node from the sink.
during continuous monitoring of vital signs in elderly patients; there is a possibility of emergency data loss during the disconnection period. It will affect the reliability of the device. Data loss can be due to either overflow of the sensor node's memory space or due to battery drainage. Schemes like parasitizing schemes [7] are implemented utilizing Wi-Fi for temporary storage to prevent data loss. But the energy consumption is approximately thrice while implementing the scheme. Here, the Hidden Markov Model (HMM) has been developed, focusing on emergency data detection and energy conservation of sensor node during temporary disconnection of wireless body area networking devices[8][9]. Here the monitoring of vital signs of heart rate and blood pressure is considered the fact that these vital parameters are highly correlated [10], and prediction is possible with high accuracy. Section 2 discusses the related work on vital sign monitoring using Hidden Markov Model and our contributions. The model is explained in detail in section 3, starting from data preparation to the classification of sequences into critical and normal models. The results are also shown with an accuracy of prediction 0.9 to 1.0. How the model can support energy conservation and reliability during the disconnection period is discussed.

2. Related work and our contributions

Home-based real-time health monitoring systems [1][11] can play a significant role in obviating many healthcare challenges like frequent hospital visits, hospitalization discomforts, healthcare costs, etc., that elder people encounter. In the present situation of covid-19 coronavirus disease, studies have found that hypertension can even cause mortality [12] in corona infected elderly patients. So it is important to foster the acceptance of wireless body area networking technology [2] in older people. Since most wireless body area networking devices work on battery, it is important to improve the energy efficiency and reliability of the monitoring devices. The paper focuses on developing a Hidden Markov Model (HMM) model for emergency data detection during temporary disconnection of sensor node from the sink and how it can be beneficial from an energy conservation point of view. A detailed review of already existing Hidden Markov Models (HMMs) applied in wireless body area networks for home monitoring applications [14][15][16] are done.

The Hidden Markov Model has been developed in [15][16] to predict the abnormality in future using present and past vital sign measurement values. The model utilizes the temporal correlation between multiple vital signs to predict abnormality. The continuous data is transmitted to the cloud using a mobile device, and the probability of occurrence of a clinical event in future is predicted. If any disconnection happens between the sensor nodes and sinks (mobile phone), the data cannot transmit the data continuously, and abnormality prediction becomes impossible. A large amount of energy has been utilized in sending information continually into the cloud for classification. The modelling of blood pressure data [17] is done using HMM to predict acute hypotension. The temporal trends in the blood pressure data before the event predict hypotension in the model. The classifier is trained using data set from the patients with hypotension and without hypotension. In [18], the abnormalities in blood sugar levels are detected by training the Hidden Markov Model with normal blood glucose measurements.

The HMM is used in the already existing models to predict the abnormality by using present and past values of multiple vital sign correlation between vital parameters. Here a novel approach to emergency detection and energy conservation using HMM has been made considering the temporary disconnection of the sensor node from the sink.

- The model is developed focusing on patients with elevated heart rate and blood pressure readings. A probabilistic HMM has been developed to predict the simultaneous happening of tachycardia and hypertension during the disconnection. The hidden states, i.e. the state of pressure readings, are estimated using highly correlated heart rate vital parameter. The dynamic threshold values are used to determine the states of vital parameters before the disconnection.
happens. For the practical applicability of the model, real data is collected from the MIMIC - II numeric datasets [13] with patients with elevated heart rate and blood pressure values.

- From the energy conservation point of view, instead of storing and transmitting the complete data packets, the emergency data can be preserved and transmitted when the connection regains. Since the model can estimate the state of pressure reading from the heart rate data, can avoid the separate monitoring of individual vital parameter during disconnection. The energy consumed by the sensing subsystem is significant compared to sporadic sensing if considering continuous monitoring.

3. Development of the model

Since simultaneous happening of tachycardia and hypertension may cause cardiovascular problems in elderly patients, it is important to detect such data and store the data without loss. Suppose we are considering the scenario of temporary disconnection of sensor node from the sink during continuous monitoring of vital signs in elderly patients. In that case, there is a possibility of emergency data loss during the disconnection period. The data loss may be caused due to the complete energy depletion of the sensor node. The model focuses on preventing emergency data loss and energy conservation during the temporary disconnection period of the sensor node.

The model is developed considering the heart rate is a major correlate of blood pressure, and heart rate can predict the development of hypertension in patients with elevated blood pressure values. The dynamic threshold limit determined using the values of vital signs before the disconnection decides the model's state change. The heart rate readings are taken as the observation sequences, and the states of pressure readings are considered the hidden states. When tachycardia happens during the disconnection period, the pressure states can be normal or hypertension. Separate models are trained using tachycardia-normal sequences and tachycardia–hypertension sequences. The probability of the observation sequence for each model is estimated. And the sequences are classified into the model with a high probability of observation sequence. The hidden states are predicted using the model parameters. The states are predicted with accuracy between 90% and 100%. The model can conserve the sensor node's energy by transmitting the critical data instead of complete medical data when the connection regains. The energy spends for separate monitoring of individual vital parameters are also be avoided.

3.1 Hidden Markov Model

The Hidden Markov Model (HMM) is a stochastic model [19], an extension of the Markov chain. The HMM is flexible with a good mathematical foundation [8] and is most suitable for the problem considered because this can use temporal trends in sequential data for modelling. The main parameters that characterize the HMM are transition probability matrix (A), emission probability matrix (B), initial probability matrix (π), number of hidden states (N), and number of observation states (M). Hidden states cannot be observed directly, but it is correlated to the observation sequences. The transition probability of one hidden state to another is represented using the transition probability matrix (A). The N number of distinct hidden states are \( S = \{ S_1, S_2, S_3, \ldots S_N \} \) and state at time \( t \) is denoted as \( q_t \). The transition probability matrix, \( A = \{ a_{ij} \} \) [9]

\[
a_{ij} = P(q_{t+1} = S_j / q_t = S_i), 1 \leq i, j \leq N.
\]

The M number of observable states of the model \( V = \{ v_1, v_2, v_3, \ldots v_M \} \). The probability of emission of observable state \( v_k \) from hidden state \( S_j \) is denoted as emission probability matrix, \( B = \{ b_{jk} \} \)

\[
b_{jk} = P(v_k \text{ at } t / q_t = S_j), 1 \leq j \leq N, 1 \leq K \leq M.
\]
The probability that the process starts with a particular initial state is the model's initial probability distribution. Here, the initial state of the developed model is taken as normal. The states of the sequences are decided using dynamic threshold limits found using the samples before the disconnection happens. The models are trained using samples with tachycardia-hypertension and tachycardia-normal values during the disconnection. Thus, the initial model parameters $\lambda_0 (A_0, B_0, \pi_0)$ are estimated for both the models. The known observation sequence and the model parameters support the re-estimation of the parameters $\lambda_1 (A_1, B_1, \pi_1)$ using the hmmtrain function. Using forward-backward algorithm, the probability of the observation sequence for each model is estimated. The sequence can be classified according to the value of the probability of observation of each model. The state of pressure readings can be estimated using the Viterbi algorithm. Here in the model, hidden sequences are predicted with good accuracy.

### 3.2 Data preparation and experimental setup

For the practical applicability of the model, the real-time data is collected from MIMIC-II numeric datasets [13]. Since the temporary disconnection period of ten minutes is considered in the model, sequences of ten minutes length are collected in excel with one sample per minute. The samples are collected carefully with initial normal readings and critical event happening within the ten minutes duration. About 200 sample sequences are collected for model development. Then the collected samples are quantized and imported to Matlab for further processing.

In [9] already developed model fixed threshold limit has been used for the state change. Here dynamic threshold limit [20] has been used for better adaptability of the model due to physiological variations in the patient's health condition. Finding the dynamic threshold values of about a hundred data samples of both heart rate and blood pressure data just before the disconnection happens. The threshold for state change is found using the three-sigma limit given by equation (3)

\[
Threshold = mean + (3 \times \text{standard deviation})
\]

If the values go beyond the limit, the change of state is estimated. This use of dynamic threshold limit helps to make the model more flexible. So it applies to all patients with an abnormality in the vital sign readings. During the disconnection period, if the vital sign values increase beyond the threshold limits shows an anomaly. Threshold values taken for different samples taken are shown in the table 1.

| Observation sequence (HR) | Hidden sequence (BP) | Threshold f $T_{HR}$ | Threshold f $T_{BP}$ |
|---------------------------|----------------------|----------------------|----------------------|
| [1,1,2,2,2,2,2,2,2,2]     | [1,1,2,2,2,2,2,2,2,2] | 111.6                | 125.2                |
| [1,1,1,1,1,1,2,2,2]      | [1,1,1,1,1,2,2,2,2,2] | 137.8                | 155.2                |
| [1,1,2,2,2,2,2,2,1,1]    | [1,1,2,2,2,2,1,1,1,1] | 102.6                | 117.1                |
| [1,1,2,2,2,2,2,2,2,2]…  | [1,1,2,2,2,2,2,2,2,2] | 112.9…              | 134.9…               |
| …                        | …                    | …                    | …                    |
The mean and the standard deviation is found from the samples of data before the disconnection happens. Using the three-sigma limit, the threshold is calculated for both the heart rate and the pressure readings. The states of the sequences are determined using the threshold values. If the value of samples goes beyond threshold, parameters are considered to be abnormal. In the figure 1 the upper threshold limit is beyond 120mmHg for pressure readings.

3.3 Training of the model

For training the model, the parameters $\lambda$ ($A$, $B$, $\pi$) should be estimated where $A$ is the transition probability matrix, $B$ is the emission probability matrix, and $\pi$ is the model's initial probability distribution. The initial parameters are estimated using hmmestimate Matlab function. With the known observation sequences and initial model parameters, the model can be trained using the Baum-Welch algorithm. The hmmtrain function re-estimates the parameters in order to optimize the parameters to get best-trained model. The model is trained using sequences with tachycardia-hypertension happening together during the interval and also with tachycardia-normal sequences.

3.4 Classification of sequences

Classification of the sequences into different models is possible using forward-backward algorithm in HMM. During the disconnection period, when tachycardia happens in the heart rate sensor, there is a possibility of normal readings in the pressure sensor and a possibility of hypertension. If tachycardia and hypertension happen together, it may cause serious heart problems in older people. In such situations, the data has to be treated as critical and to be saved. The HMM is trained using sequences with tachycardia and hypertension happenings and sequences with tachycardia and normal pressure readings. The data has been collected from MIMIC II numeric datasets [13] for realistic application. The probability of observation sequence in the critical data model is found and compared with the likelihood of observation sequences in the normal model for detecting the sequences with critical events. The separate models are trained, and classification is plotted in the figure below. Here about ten sequences are used for classification where the sequences are with critical happenings. As shown in figure 2, the sequences are classified into the model with a higher probability of observation.
Figure 2 The classification of sequences with tachycardia-hypertension happening together during disconnection. The sequences are classified into model with higher value of logpseq.

3.5 Decoding of the model

From the re-estimated model parameters, the most probable hidden states can be estimated using the Viterbi algorithm. Likely states predicted are compared with the hidden states taken for testing and can estimate the accuracy of the model. The figure plots the hidden sequences taken for testing and predicted likely states. An accuracy of 1 is obtained for sequence1 and an accuracy of 0.9 for sequence2, as shown in figure 3 below.

Figure 3. Comparing the known test hidden sequence with predicted likelihood states of blood pressure readings for sequence 1 and sequence 2.

4. Conclusion

The HMMs are a flexible model which supports the temporal trends in sequential data, and it suits the problem considered for the model development. The model has been developed mainly considering patients with elevated blood pressure and heart rate readings. The vital parameter heart rate is taken as the observation sequences and blood pressure state as the hidden states. The model states are decided using a dynamic threshold limit found using the samples of vital parameters before the disconnection happens. During the disconnection period of ten minutes, when tachycardia is observed in the sensor node, there is a possibility of hypertension or normal state of pressure readings in the patient. The models are trained with sequences tachycardia-hypertension and tachycardia-normal states using real
samples of patients collected from the physiobank archive. The observation sequences are classified by comparing the probability of observation in particular models. After classification, the hidden states are estimated using the Viterbi algorithm. Dynamic threshold limits can support the patients' varying physiological conditions, and states can be estimated depending on the parameter values before the disconnection. Here we had considered the patients with elevated heart rate and blood pressure values. The model can also detect abnormal states like hypotension since it can apply dynamic threshold limits in the lower values. Further, it is possible to extend the model into lower critical states also.

From the energy conservation point of view, the energy can be conserved by transmitting only the critical data when the connection regains instead of complete medical data. The energy can also be conserved by avoiding separate monitoring of individual vital parameters. Especially for continuous monitoring scenarios, the sensors can consume more energy compared to sporadic sensing.

Since the improvement in the reliability and energy efficiency of vital sign monitoring devices can foster the acceptance of this technology by elderly patients, this paper can contribute a significant role in geriatric care applications. The model can predict the critical event and classify the sequences with good accuracy between 0.9 and 1. In the present covid19 pandemic situation, the importance of remote vital sign monitoring cannot be overstated.

5. References

[1] Majumder S, Aghayi E, Noferesti M, Memarzadeh-Tehran H, Mondal T, Pang Z and Deen MJ 2017 Smart Homes for Elderly Healthcare—Recent Advances and Research Challenges *Sensors* **17**(11):2496

[2] S. Movassaghi, M. Abolhasan, J. Lipman, D. Smith and A. Jamalipour, 2014 Wireless body area networks: A survey, *IEEE Communications Surveys & Tutorials*, vol. **16** no. 3, pp. 1658—1686

[3] B. Latr’ e, B. Braem, I. Moerman, C. Blondia, and P. Demeester 2011 A survey on wireless body area networks,*Wireless Network*, vol. **17**, pp. 1–18.

[4] Tifenn Raut, Abdelmadjid Bouabdallah, Yacine Challal, 2014 Energy efficiency in wireless sensor network: A top- down survey, *Computer networks*, vol. **67**, pp.104-122.

[5] G. Anastasi, M. Conti, M. Francesco, A. Passarella, 2009 Energy Conservation in Wireless Sensor Networks: A survey, *Ad Hoc Networks*, Vol. **7**, Issue 3, pp. 537-568.

[6] Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, 2002 Wireless sensor networks: A survey, *Computer Networks*, vol. **38**, no. 4, pp. 393–422.

[7] Yuan-Yao Shih , Pi-Cheng Hsiu and Ai-Chun Pang , Data Parasitizing Scheme for Effective Health Monitoring in Wireless Body Area Network, *IEEE TRANSACTIONS ON MOBILE COMPUTING*, Vol. 18, no. 1, pp. 13-27, 2019.

[8] R. R. Pillai and R. B. Lohani, 2020 “Abnormality Detection and Energy Conservation in Wireless Body Area Networks using Hidden Markov Models: A Review,” *International Conference on Communication and Signal Processing (ICCSP)*, Chennai, India , pp. 0935-0939.

[9] R. R. Pillai and R. B. Lohani, “Emergency data detection using Hidden Markov Model during temporary disconnection of Wireless Body Area Networks,” *International Conference for Emerging Technology (IN CET)*, Belgaum, India, 2020, pp. 1-5

[10] Paolo Palatini and Stevo Jukus, “Heart rate the and cardiovascular risk”, *Journal of Hypertension*, vol.15, No.1, pp.3-17, 1997

[11] Al-khafajy M, Baker T and Chalmers C 2019 Remote health monitoring of elderly through wearable sensors. *Multimed Tool Appl.*, **78**, 24681–24706.

[12] Giuseppe Lippi, Johnny Wong, Brandon Michael Henry, "Hypertension and its severity or mortality in Coronavirus Disease 2019 (COVID-19): a pooled analysis", *Article in Polskie archiwum medycyny wewnętrznej*, March 2020

[13] https://archive.physionet.org/cgi-bin/atm/ATM

[14] R. M. Forkan, I. Khalil, Z. Tari, S. Foufou, A. Bouras, 2015 “A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living”, *Pattern Recognition*, vol. 48, pp.628-641.
[15] R. M. Forkan, I. Khalil, “A probabilistic model for early prediction of abnormal clinical events using vital sign correlations in home-based monitoring”, IEEE International Conference on Pervasive Computing and Communications (PerCom), pp. 1-9, 2016.

[16] ARM Forkan, I. Khalil, "PEACE-Home: Probabilistic Estimation of Abnormal Clinical Events using vital sign correlations for reliable Home-based monitoring", Pervasive and Mobile Computing, vol.38, part 2, pp. 296-311, 2017

[17] Singh A, Tamminedi T, Yosiphon G, Ganguli A, Yadgar J, "Hidden Markov Models for modeling blood pressure data to predict acute hypotension", Acoustics Speech and Signal Processing (ICASSP),IEEE International Conference, p.p 550–553, 2010.

[18] Y. Zhu, "Automatic detection of anomalies in blood glucose using a machine learning approach," in Journal of Communications and Networks, vol. 13, no. 2, pp. 125-131, April 2011

[19] L. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," Proceedings of the IEEE, vol. 77, no. 2, pp. 257 - 285, Feb. 1989.

[20] Haque, S.A., Rahman, M., Aziz, S.M. “Anomaly Detection in Wireless Sensor Networks for Healthcare.” Sensors, Vol. 15, p.p 8764-8786, 2015