HEART RATE MONITORING IN NEONATAL INTENSIVE CARE USING MARKOV MODELS

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ABSTRACT

Although heart-rate is commonly measured in various clinical settings the advanced algorithms for its prediction are rarely implemented in clinical settings and patient management. In neonatal intensive care timely prediction of dangerous levels of heart rate can lead to improved care, long-term effects and reduced morbidity. In this paper we propose to model the heart-rate using Markov chain model and estimate transition probabilities using maximum likelihood estimator and the patient population from Neonatal Intensive Care Unit at McMaster Hospital. The probabilities of reaching high-risk states in predetermined time intervals are computed and the results are evaluated using the real data set.

Index terms: Neonatal intensive care, Markov chains, Heart-rate prediction.

1. INTRODUCTION

A new approach in neonatal intensive care is continuous monitoring of multiple streams of newborn information with the goal of rapid diagnosis/detection of pathological conditions. Although very appealing this approach has not been often applied in practice in many hospitals. In addition to technical challenges there still remains variety of clinical issues such as which modalities are most useful in predicting various pathological conditions.

It has been recently proposed that heart-rate characteristics may play important role in predating the onset of conditions such as sepsis, systemic inflammatory response syndrome (SIRS) etc [1]. This is especially important since each year more and more prematurely born babies have very low birth weight which require prolonged hospitalization for ventilation and feeding, and despite improvements in neonatal intensive care may experience significant complications such as sepsis, inflammation, etc [2]. The National Institute of Health has stated that strategies to reduce the incidence and severity of neonatal sepsis are needed urgently. [3].

In this paper we propose a signal processing framework for monitoring and predicting neonatal heart rates Markov Chain models. Heart rate and its variability have served as one of the most reliable and authentic methods of testing the state of human heart. It has been a subject of considerable interest which resulted in variety of different techniques such as non-Markov processes [4], entropy [5], Hidden Markov Models [6]. In this study however we focus on developing monitoring tools for assisting physicians in making clinical decisions in the neonatal intensive care unit (NICU). To this purpose we propose to model heart-rate using finite-state Markov Model consisting of four states. We then derive the maximum likelihood estimator of the unknown transition probabilities. Since biomedical signals are most often stationary in a time-window of relatively short length we account for the finite sample-size by modeling the count of transitions as multinomial random variable and derive the corresponding MLE estimates. We then evaluate the performance of the proposed technique using a real measurement obtained at NICU McMaster Hospital. Herein we review and report our current findings and efforts to date.

The paper is organized as follows. In Section II we describe the signal model and describe the Markov Model. In Section III we derive the statistical distribution of the measurement data and the corresponding ML estimator. In Section IV we illustrate the applicability of our results using a data set consisting of two hundred neonatal patients. Section V concludes the paper.

2. SIGNAL MODEL

This work is based on the analysis of a digital recordings of neonatal heart-rate using Drager Medical Infinity system. The sampling interval was set to 1 minute. For each patient we continuosly recorded the data throughout their stay at the NICU and thus the length of data segments varies from patient to patient.

According to specifications provided by clinicians there are four regions of interests with respect to the heart rate: a) low rate high risk (LRHR) for heart rates below 80 beats per minute, b) normal rate for heart rates between 80 and 100 beats per minute, c) high rate low risk for heart rates between 100 and 150 beats per minute, and d) high rate high risk for heart rate above 150 beats per minute. In Figures 1 and 2 we illustrate the heart-rate time series of two randomly selected patients with 33 and 35 weeks of gestation respectively during their third day of stay in the intensive care. In Figures 3 and 4 we illustrate the corresponding state histogram of the same two patients.

To formulate the Markov model we first assert that in this case the states corresponding to heart rates are directly observable. Next let $h_i(t_j)$ be the heart rate of patient i at sampling time j and let S_{ij} be the state of the ith patient at time t_j. We assert

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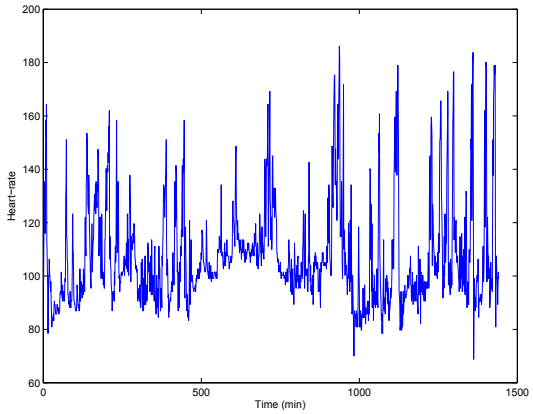

Fig. 1. Heart rate time series – 33 weeks of gestation.

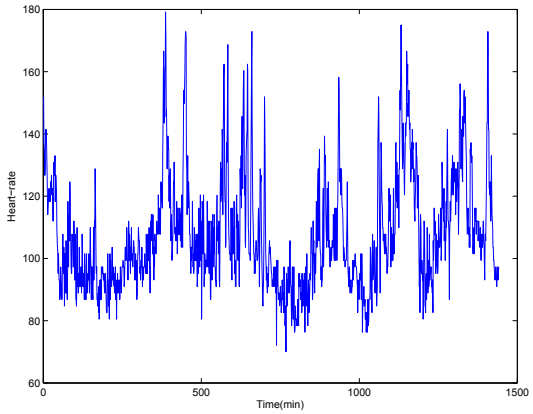

Fig. 2. Heart rate time series – 35 weeks of gestation.

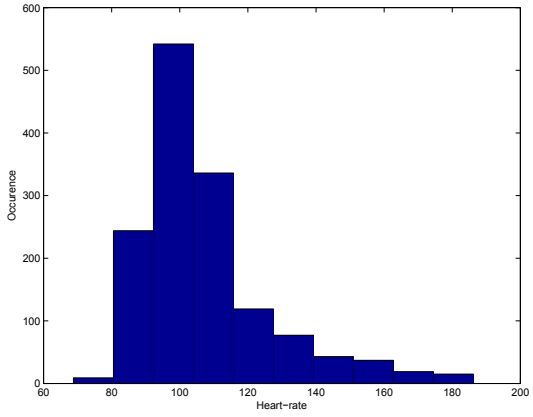

Fig. 3. State distribution – 33 weeks of gestation.

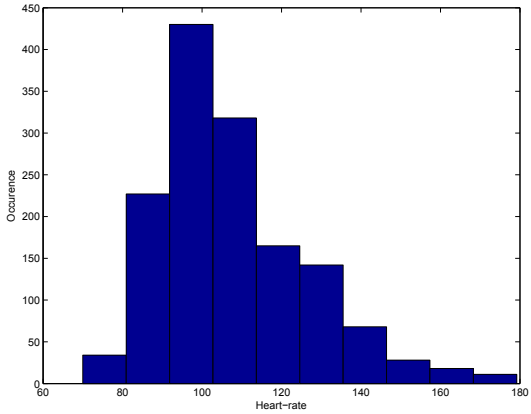

Fig. 4. State distribution – 35 weeks of gestation.

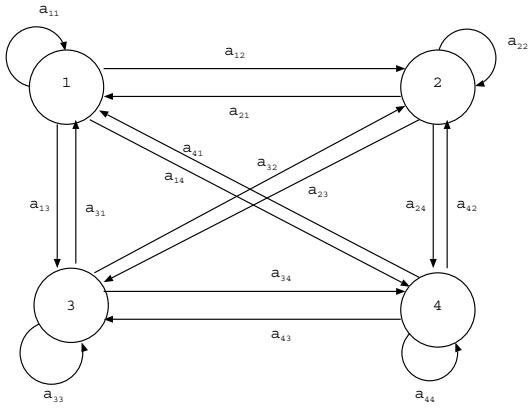

Fig. 5. Markov Chain model scheme – 4 states

that at any time the patient can be in one of the following states

$$S_{ij} = \begin{cases} Q_1 & h_i(t_j) < 80 \\ Q_2 & 80 \leq h_i(t_j) < 100 \\ Q_3 & 100 \leq h_i(t_j) < 150 \\ Q_4 & 150 \leq h_i(t_j) \end{cases}$$

We assume that the Markov chain is first order and therefore the transition probabilities for the ith patient are given by

$$a_{kl}^i = \Pr[S_{ij+1} = Q_l | S_{ij} = Q_k] \quad 1 \leq k, l \leq 4 \qquad (1)$$

Note that we use superscript i to denote that the transition probabilities are patient dependent i.e., they change across the population. Furthermore due to the development process these transition probabilities are time dependent i.e., the process is non-stationary. However, during window of several hours we do not expect significant changes therefore we divide data segments in overlapping windows of six hours size with fifteen minutes time shifts. In Figure 5 we illustrate our Markov chain model used in this work.

3. PARAMETER ESTIMATION

In order to construct the transition diagram of our Markov model we need to estimate the state transition probabilities using maximum likelihood criterion. We first that the measurement data for this estimation problem are given by transition counts.

Let n_{kl}^i be the number of transitions for the ith patient in a particular data segment d from state Q_k to state Q_l. Then all the transitions from state k are given by $n_k^i = \sum_{l=1}^4 n_{kl}^i$. In order to obtain the maximum likelihood estimator in the case of finite size chain one would have to obtain probability density functions of n_{kl}^i and n_k^i. These pdfs can be computed using Chapman-Kolmogorov forward equation [7] which define probabilities of going from stage k to stage l in p steps denoted by $a_{kl}^{i,p}$. It can be shown [7] that $a_{kl}^{i,p}$ can be obtained as (k,l) entry of matrix A^p where $A = [a_{kl}^i]$ is the transition state matrix for the ith patient. These probabilities can then be used to compute the required pdfs. However when the chain size is large it has been shown that the frequency count converges to maximum likelihood estimate. In the remainder of the paper we assume that the maximum likelihood estimates are given by

$$\hat{a}_{kl}^i = \frac{n_{kl}^i}{n_k^i} \tag{2}$$

Using the above estimators we obtain the following transition matrix estimates for the aforementioned two patients. For the first patient we get

$$\begin{bmatrix} 0.9128 & 0.0872 & 0 & 0 \\ 0.1032 & 0.863 & 0.0229 & 0.010921 \\ 0 & 0.011372 & 0.96478 & 0.023848 \\ 0 & 0.01 & 0.02179 & 0.96826 \end{bmatrix} \tag{3}$$

and for the second patient

$$\begin{bmatrix} 0.4867 & 0.5133 & 0 & 0 \\ 0.1488 & 0.5495 & 0.1621 & 0.1396 \\ 0 & 0.3401 & 0.3217 & 0.3382 \\ 0 & 0.3285 & 0.3405 & 0.3310 \end{bmatrix} \tag{4}$$

The fact that the above models are discrete time stationary, ergodic Markov chains allows us to perform various statistical analysis. More importantly using estimated transition matrices we can, for each patient, compute probability that he/she will go from low risk state to one of the high risk states for a given period of time which can significantly improve quality of care.

4. NUMERICAL RESULTS

To evaluate the applicability of the proposed model for the prediction of heart-rate we first obtained a data set by monitoring the heart rate of 186 patients at NICU at McMaster Hospital. Then, for each patient we estimated data transition matrix using a six hours window at the beginning of the day and then used these estimates to compute the probability of transition

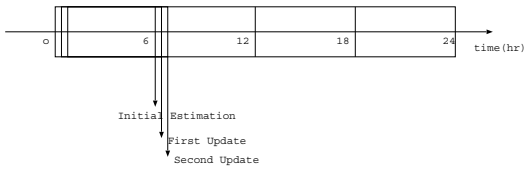

Fig. 6. Performance Evaluation Scheme

to high-risk states. After fifteen minutes we update the estimates of transition probability using an overlapping window as illustrated in Figure 6.
To evaluate the performance of our Markov chain model we proposed the following algorithm.

- For each time step we compute the probability that the patient will reach one of high-risk states using Chapman-Kolmogorov equation.
- If the probability of reaching the high-risk state is larger than threshold τ we generate an alarm.
- We use the estimation window as a training set to select τ for a given probability of false-alarm.
- We evaluate the probability of miss i.e., alarm was not generated and patient reached the high-risk state.

In Figure 7 we illustrate the probability of error (miss) as a function of the prediction step for all the patients with 33 weeks of gestation. In Figure 8 we illustrate the same results but for patients with 35 weeks of gestation. In both examples we assume the false-alarm rate of 15%. Note that the gestation period for all the patients admitted to NICU at McMaster hospital during the experiment ranged from 32 weeks to 39 weeks. However, the largest population was seen for weeks 33 and 35 (45 and 50 patients respectively) and thus we chose to test the proposed model using these two groups.

As it can be seen our model performs slightly better in newborns with longer gestation. This is expected due to higher level of physiological development. Using these results we can design a custom system, with predetermined levels of false alarms in desired time frame and thus enable physicians tools to optimize decision making in intensive care.

5. CONCLUSIONS

The essence of the continuous monitoring in neonatal intensive care (NICU) is to detect dangerous states and alarm medical staff. However, in recent years predicting the onset of these states (e.g., high and low heart rates) gained increasing interest as part of effort to reduce mortality rates and long-term effects by timely intervention. In this paper we proposed a theoretical framework using Markov Model which can be used for predicting the likelihood of reaching dangerous heart-rates in predetermined time steps. The transition probabilities are estimated using maximum likelihood and are then continuosly updated in fifteen minutes increments which is necessary as the model parameters may change with time. We then evaluated the performance of the proposed model for predicting the

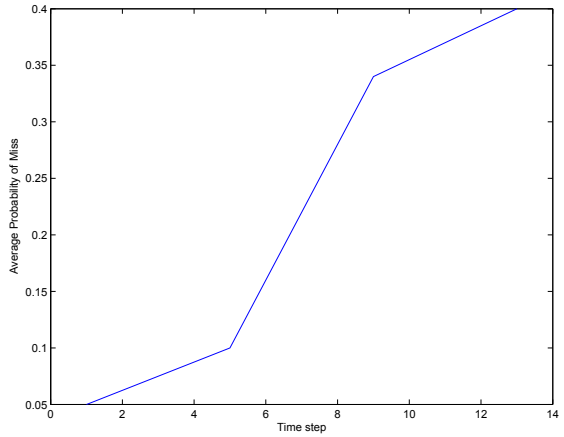

Fig. 7. Average probability of miss for 33 weeks of gestation.

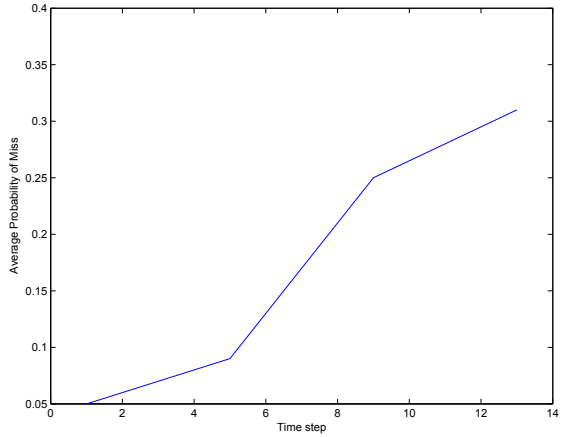

Fig. 8. Average probability of miss for 35 weeks of gestation.

likelihood of reaching the high risk states using Kolmogorov-Chapman equations. Our preliminary results indicate that this approach can potentially be useful since it provides acceptable levels of false alarm and miss but enables medical staff to optimize decision making and treatments.

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