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Neonatal Heart Rate Prediction

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Abstract— **Technological advances have caused a decrease in the number of infant deaths. Pre-term infants now have a substantially increased chance of survival. One of the mechanisms that is vital to saving the lives of these infants is continuous monitoring and early diagnosis. With continuous monitoring huge amounts of data are collected with so much information embedded in them. By using statistical analysis this information can be extracted and used to aid diagnosis and to understand development. In this study we have a large dataset containing over 180 pre-term infants whose heart rates were recorded over the length of their stay in the Neonatal Intensive Care Unit (NICU). We test two types of models, empirical bayesian and autoregressive moving average. We then attempt to predict future values. The autoregressive moving average model showed better results but required more computation.**

I. INTRODUCTION

Pre-term infants are especially fragile and in need of care. Their hearts are usually not fully developed and need constant monitoring. Modeling neonatal heart rate data can aid in understanding development and diagnosing conditions such as neonatal sepsis [1]. If a good model is found, forecasting future values can enhance the performance of monitoring devices by decreasing the number of false alarms [2] and early detection of stress. Medical Literature has indicated a relationship between heart rate variability and the condition of an infant [3] [4] but prediction of neonatal heart rate has not been attempted. We analyze a dataset containing over 180 pre-term infants whose heart rates were recorded over the length of their stay in the Neonatal Intensive Care Unit (NICU). These heart rates were collected at a sampling rate of one minute, which is the common sampling rate in clinical setting. The aim of our study is to find a suitable model that can be used to predict future values.

This paper is organized as follows, in Section II the models used are briefly described, Section III contains notes on the estimation of model parameters and prediction methods, Section IV presents the results and finally Section V concludes the paper and includes future venues to be investigated.

II. SIGNAL PROCESSING MODELS

A. Autoregressive Moving Average

Autoregressive Moving Average (ARMA) is a type of stochastic process that consists of two parts, autoregressive and moving average. As for the first part, it is a process where observation at time t is represented as a weighted average of the most recent p number of observations where p is the length of AR. The moving average part describes the effect of the q most recent random disturbances on the observation at time t. Put together we have an ARMA(p,q) process where both past observations and past random disturbances affect current observations. [5] The following equation represents a general ARMA(p,q) model where α_i are the weights for the previous observations in the time series $x(t)$ and β_i are the weights for the previous values of the random noise signal $e(t)$.

$$x(t) = \sum_{i=1}^{p} \alpha_i \; x(t-i) + \sum_{i=1}^{q} \beta_i \; e(t-i) + e(t) \qquad (1)$$

Noise signal, $e(t)$, is modeled as a series of independent identically distributed random variables with zero mean and unknown variance. This is regarded as the input to the system, as the input cannot be measured [6].

B. Empirical Bayesian Model

Performing a differencing transformation on a time series is a common practice in signal processing. It is usually done to remove trend, dc component or a slowly varying mean. Autocorrelation shows a different pattern after a differencing transformation which helps in modeling the signal. A sample of the heart rate signal from one patient is shown in Fig. 1. Fig. 2 shows the autocorrelation of the original signal while Fig. 3 shows autocorrelation after differencing. Differencing may be repeated more than once to reveal the underlying process.

In this model we use the distribution of these differences to predict future heart rate values.
Let

$$v_\alpha(t) = hr(t) - hr(t-\alpha); \qquad (2)$$

where $hr(t)$ is the heart rate signal at time t.

The heart rate signal at time $t+\gamma$ is $\widehat{hr}(t+\gamma) = hr(t) + \widehat{v_\gamma}(t+\gamma)$.

$$\begin{aligned} &\widehat{v_\gamma}(t+\gamma|t,t-1,\ldots,t-\rho) = \\ &_{argmax}\mathbf{P}(v_\gamma(t), v_1(t), v_1(t-1), \ldots, v_1(t-\rho)); \end{aligned} \qquad (3)$$

where ρ is the length of the predictor, γ is the number of steps ahead for the estimation and $\mathbf{P}$ is a multilevel histogram ie multidimensional matrix whose entries are updated as follows.

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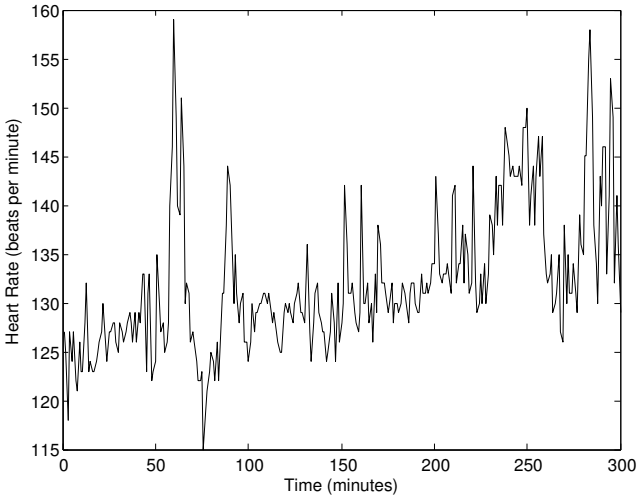

Fig. 1. Sample Heart Rate

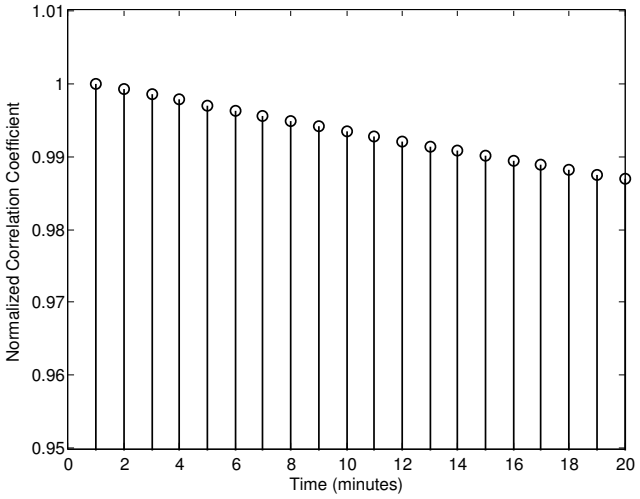

Fig. 2. Heart Rate Correlation Coefficients

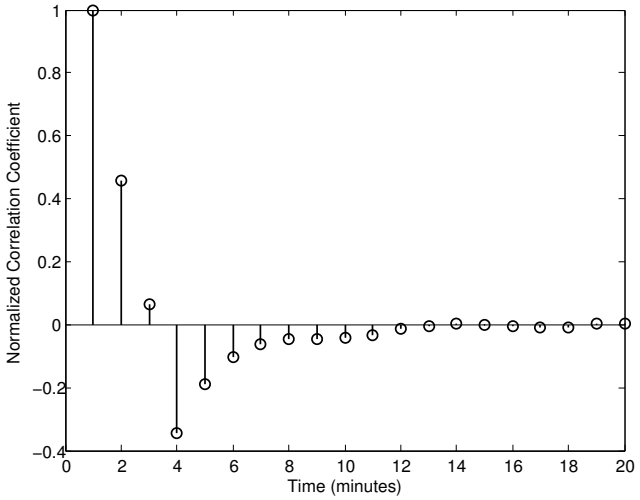

Fig. 3. First Derivative Correlation Coefficients

Matrix **P** has $\rho+1$ dimensions each of size $|v_{min}|+v_{max}+1$. In the training period we find $v_\gamma(t), v_1(t-\gamma), v_1(t-\gamma-1), \ldots, v_(t-\gamma-\rho)$. For time t the following matrix entry is incremented:

$$v_\gamma(t)+m, v_1(t-\gamma)+m, v_1(t-\gamma-1)+m, \ldots, v_1(t-\gamma-\rho)+m;$$

where $m=|v_{min}|+1$ which is a variable used for mapping.

The maximum and minimum values of $v_1(t)$ for a number of patients were found and after removing outliers we selected v_{min} and v_{max}.To maintain low dimensionality of matrix **P** postprocessing is done on the entries such that

$$v_\alpha(t) = \begin{cases} min(v_\alpha(t), v_{min}) & v_\alpha(t) < v_{min} \\ max(v_\alpha(t), v_{max}) & v_\alpha(t) > v_{max} \end{cases}$$

More than one combination of differences may occur the same number of times thus Eq.3 may return multiple values. To resolve such situations we propose using another matrix **SV**. This matrix has 6 dimensions each of size $|v_{min}|+v_{max}+1$. The heart rate signal $hr(t)$ is classified into one of the following states:

$$S(t) = \begin{cases} 1 & hr(t) \leq 100 \\ 2 & 100 < hr(t) \leq 120 \\ 3 & 120 < hr(t) \leq 140 \\ 4 & 140 < hr(t) \leq 160 \\ 5 & 160 < hr(t) \leq 180 \\ 6 & 180 < hr(t) \end{cases}$$

For time t the following matrix entry is incremented:

$$S(t-\gamma), v_\gamma(t)+m$$

This matrix relates $v_\gamma(t)$ to the state of $hr(t-\gamma)$ because it is expected that the change in heart rate is related to the range in which the previous heart rate is.

C. Model Evaluation

For each day a patient stayed in the NICU there is an array of 1440 heart rate samples, $hr(t)$. To test the aforementioned models, the heart rate data for each patient was divided into a training segment and testing segment.

The number of days used for training was varied and the model parameters $\gamma, \rho, \alpha, \beta$ were varied.

The models were then used for prediction and their performance was evaluated based on mean square error between the predicted value and the true value.

$$mse(t) = (hr(t) - \widehat{hr}(t))^2$$

III. Model Estimation and Prediction

A. Autoregressive Moving Average

ARMA parameters were estimated using an iterative algorithm that minimizes a robustified quadratic prediction error criterion. The algorithm stops after a maximum of 20 iterations or when improvement is not significant. The MATLAB® function `armax` is used for this estimation.

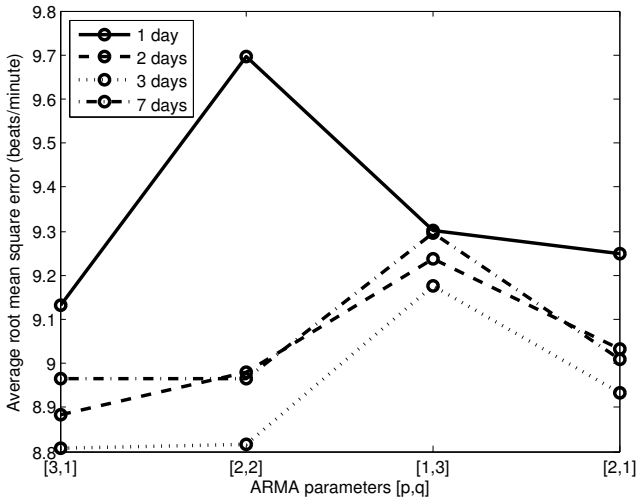

Fig. 4. 5 Step-Ahead Prediction Mean Square Error vs [p,q] variations for different numbers of training days

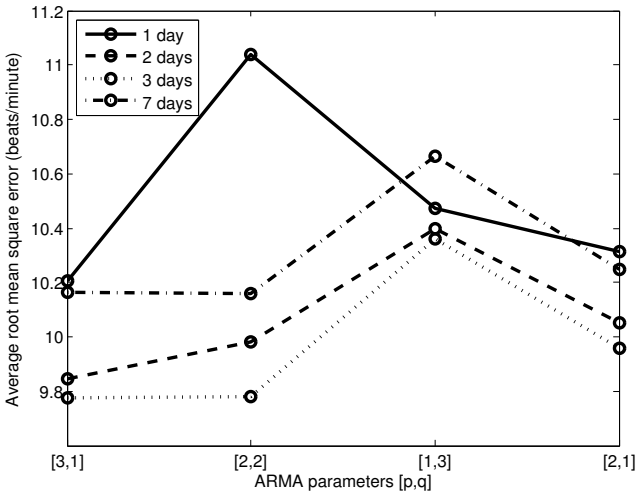

Fig. 5. 10 Step-Ahead Prediction Mean Square Error vs [p,q] variations for different numbers of training days

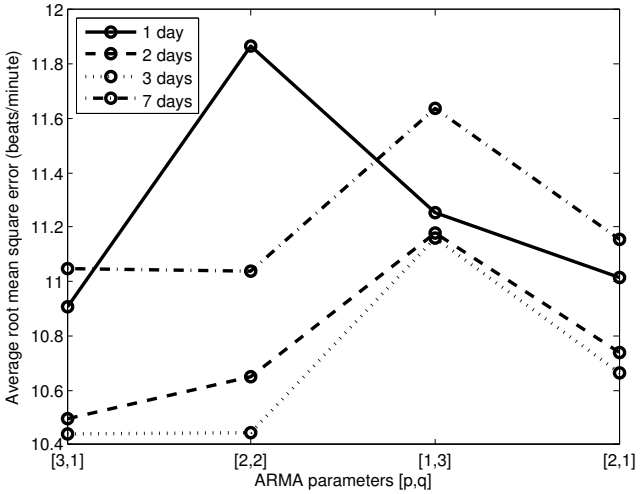

Fig. 6. 15 Step-Ahead Prediction Mean Square Error vs [p,q] variations for different numbers of training days

B. Empirical Bayesian

Heart rate data for d number of days was used to construct the aforementioned **P** matrix and **SV** matrix. The remaining data was used to test the Bayesian predictor. Future values were estimated as follows:

1) Differences $v_1(t), v_1(t-1), \ldots, v_1(t-\rho)$ are calculated.
2) Row $v_1(t)+m, v_1(t-1)+m, \ldots, v_1(t-\rho)+m$ from matrix **P** is selected
3) The index, i, of the entry with the highest value in this row is selected
4) If more than one entry have this same value the **SV** matrix is used. $hr(t)$ is classified into the appropriate state, S.
5) The index, i, of the entry with highest value in row S is picked.
6) If there is more than one entry with this same value the median is chosen.
7) $\widehat{v}_{\gamma}(t+\gamma) = i - (|v_{min}|+1)$
8) $\widehat{hr}(t+\gamma) = hr(t) + \widehat{v}_{\gamma}(t+\gamma)$

IV. Results

A. ARMA

Training to estimate ARMA parameters was done using different numbers of days. The performance for 5-step ahead, 10-step ahead and 15-step-ahead prediction was tested using the remaining days by calculating mean square error. The average of root mean square errors from all patients' data is shown in Figs. 4, 5 and 6. The lowest errors were observed when 3 days were used for training for which ARMA(3,1) and ARMA(2,2) gave similar results for all predictor lengths.

B. Empirical Bayesian

Combinations of different numbers of training days, d, past velocities ρ and prediction steps γ were tested. In Figs. 7, 8 and 9 we show the average of root mean square errors from all patients' data versus models with $\rho = 1,2,3$ for $\gamma = 5,10,15$. Performance of models with 1, 2 and 3 training days was very similar. Thus this model has the advantage of requiring less training.

V. Conclusions and Future Works

In this paper we studied the applicability of ARMA models for predicting (tracking) neonantal heart rates. We also proposed and tested a histogram based Bayesian approach. Heart rate data used is minute average and not the R-R interval derived value. R-R interval heart rate data, has a higher sampling rate and may produce better models but with most commercial patient monitors it is an additional cost to extract this data. Therefore, in order to create a practical predictor that can be used in the Neonatal Intensive Care Unit it should be based on the minute average. Our preliminary results are very promising and could be practically applicable. We have not found any other attempts to predict neonatal heart rate.

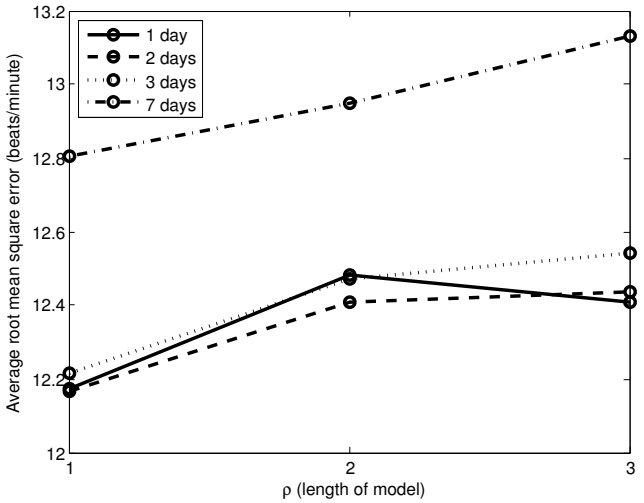

Fig. 7. 5 Step-Ahead Prediction Mean Square Error vs Model length for different numbers of training days

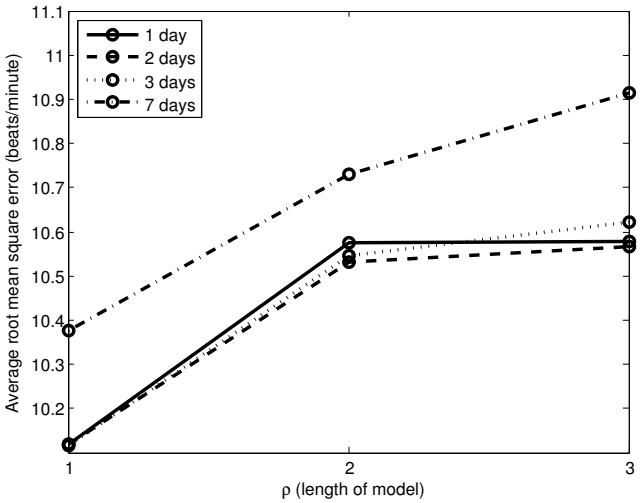

Fig. 9. 15 Step-Ahead Prediction Mean Square Error vs Model length for different numbers of training days

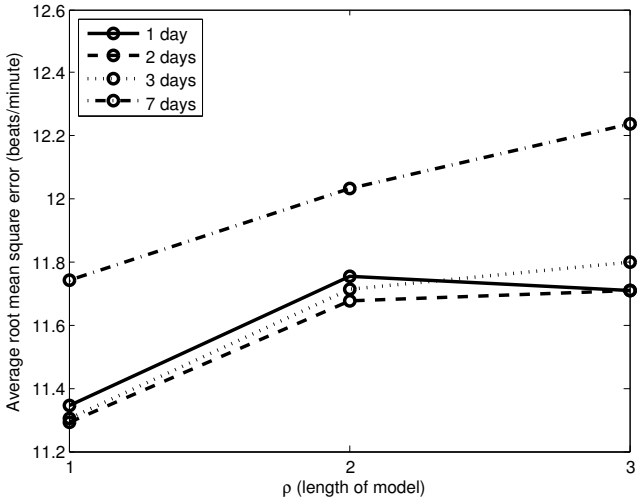

Fig. 8. 10 Step-Ahead Prediction Mean Square Error vs Model length for different numbers of training days

This study is preliminary and we plan to pursue it to get more commercially applicable results.

The results indicate that the ARMA model has smaller error than Bayesian model but larger computational complexity. In addition it seems there is an optimal length for the Bayesian approach since the error starts to increase as the length of the model increases. However the error of the Bayesian approach may be due to discretization levels used in histogram modeling. Therefore in future work we will study the discretization effects on the Bayesian approach accuracy. A priori distribution matrix **P** can be smoothed and updated for every new $hr(t)$. Estimation of **P** can also be made using data from all the patients throughout their stay. This **P** matrix can be then updated to be adapted for each patient.

Also, different window sizes can be tested for ARMA estimation which may produce better results as the data may be stationary in that window. A global estimate can be made using all patient data. This estimate can be used as an initial estimate for each patient at the beginning of monitoring and then updated appropriately. Since the data is non stationary adaptive AR modeling such as that discussed in [7] may produce better results.Other measures of model performance need to be investigated such as residual variance [6].

REFERENCES

[1] J. Moorman, D. Lake, and M. Griffin, "Heart rate characteristics monitoring for neonatal sepsis," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 1, pp. 126–132, 2006.

[2] J. Quinn, C. Williams, and N. McIntosh, "Factorial switching linear dynamical systems applied to physiological condition monitoring," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 22, 2008.

[3] C. van Ravenswaaij-Arts, L. Kollee, J. Hopman, G. Stoelinga, and H. van Geijn, "Heart rate variability," *Annals of Internal Medicine*, vol. 118, no. 6, pp. 436–447, 1993.

[4] J. Jenkins, M. REID, and B. McClure, "Study of heart rate variability in sick newborn infants," *Acta Paediatrica*, vol. 69, no. 3, pp. 393–396, 1980.

[5] R. Yaffee and M. McGee, *An Introduction to Time Series Analysis and Forecasting: With Applications of SAS and SPSS*. Academic Press, 2000.

[6] D. Christini, F. Bennett, K. Lutchen, H. Ahmed, J. Hausdorff, and N. Oriol, "Application of linear and nonlinear time series modeling to heart rate dynamics analysis," *IEEE Trans. Biomed. Eng.*, vol. 42, no. 4, pp. 411–415, 1995.

[7] M. Aboy, O. Marquez, J. McNames, R. Hornero, T. Trong, and B. Goldstein, "Adaptive modeling and spectral estimation of nonstationary biomedical signals based on Kalman filtering," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 8, pp. 1485–1489, 2005.