MODELLING PATIENT VITAL-SIGN DETERIORATION TRAJECTORIES USING BAYESIAN INFERERENCE

Sara Khalid[1], David A. Clifton[1], and Lionel Tarassenko[1]

Institute of Biomedical Engineering, Dept. of Engineering Science, University of Oxford, OX3 7DQ, U.K.

{sara.khalid, david.clifton, lionel.tarassenko}@eng.ox.ac.uk

Abstract – Vital signs recorded at the hospital bedside manually by clinical staff are key indicators of patient physiology and may be used to track patient deterioration. The low frequency of vital-sign observations by clinical staff (every 4, 8 or 12 hours) makes it difficult to determine the underlying distribution for each vital sign. In this paper we demonstrate how a Bayesian approach may be used to estimate the unknown parameters of vital sign data.

I. INTRODUCTION

Vital signs such as heart rate (HR), breathing rate, blood pressure, oxygen saturation, and temperature, are key indicators of patient condition. Understanding the behaviour of vital signs, individually and collectively, prior to an episode of patient deterioration (which can lead to an emergency admission to the Intensive Care Unit) is vital to alerting clinicians early to the impending deterioration. Typically, vital-sign data are sampled and recorded manually every four to twelve hours by nursing staff on hospital wards, and may be used to construct a model for identifying and predicting deterioration. However, the low sampling frequency makes it difficult to estimate the underlying distribution accurately. We propose to take a Bayesian approach for model parameter inference, such that the uncertainty in estimation is accounted for in a principled manner.

II. ESTIMATING THE UNKNOWN DISTRIBUTION

We initially assume the underlying distribution of a window of 5-dimensional vital-sign data, $\mathbf{X} = \{x_1, x_2, \dots x_5\}$, to be Gaussian, which is fully described by its mean and variance. The Bayesian approach to estimating a Gaussian distribution with unknown mean (μ) and precision (λ), the inverse of the variance, is described by the conjugate pair of prior $p(\mu,\lambda)$ and posterior $p(\mu,\lambda|\mathbf{X})$ distributions, which for the case of a univariate Gaussian distribution with unknown mean and variance, follows the 'normal-gamma' distribution, defined as [1]:

$$NormalGamma(\mu, \lambda | \mu_n, \beta_n, a_n, b_n) \sim Normal(\mu \mid \mu_n, (\beta_n \lambda)^{-1})\, Gamma(\lambda \mid a_n, b_n)$$

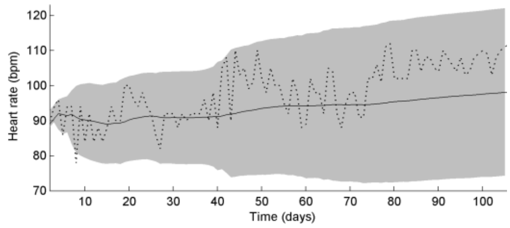

Fig. 1 Time-series of HR 'deterioration' (dotted), and estimated marginal mean HR (line), with ± estimated marginal deviation in grey

where $n = 1,2,\dots, N$ is the sample number, and a_n and b_n are the rate and shape of the Gamma distribution, respectively, which describes the distribution of the precision λ. β_n is a constant which describes the dependence of the mean on the precision.

Retrospective Patient-specific Trajectory

We initially consider one physiological variable, x_1, the heat rate. The HR data for individual patients from a database acquired from post-surgical patients in the Oxford Cancer Hospital were divided into 24-hour windows, and for each window (except the first), the previous window's posteriors were used as priors. For the first window an 'improper' prior was assumed, with $\mu_0 = 0$, $a_0 = -0.5$, $b_0 = 6$, and $\beta_0 = 0$.

Fig.1, which shows the estimated marginal posterior mean of the HR, illustrates the gradual but noticeable rise in HR as the patient deteriorates from an initial HR of 89 bpm to an estimated 98 bpm. The increasing variance illustrates a rise in estimation 'uncertainty' as deviations (e.g. the sharp rise around day 40) in the HR occur.

III. DISCUSSION and CONCLUSION

The preliminary results introduced in this paper suggest that HR deterioration can be a gradual phenomenon occurring over several days. In future, we intend to use multivariate extensions to investigate deterioration in combinations of vital signs, with more complex, multi-modal distributions.

REFERENCES

[1] C. Bishop, *Pattern Recognition and Machine Learning*, Springer, 2006.