Bayesian Condition Monitoring in Neonatal Intensive Care

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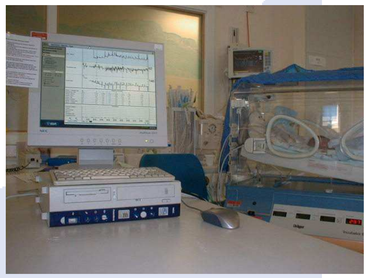
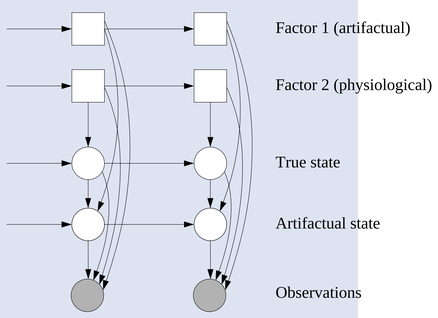
Physiological monitoring

Vital signs, literally 'signs of life', are used in neonatal intensive care to help diagnose problems in babies who are in a critical condition. These physiological measurements (e.g. heart rate or blood gas properties) are affected by many possible factors, including interventions to the baby, the operation of the monitoring equipment and the state of health. Our main aim is to be able to infer the presence of these factors from the observations automatically. We also aim to infer the times when there is a change in the dynamics of which the cause is unknown, since if these changes are not artifactual and not part of a common pattern they are likely to have clinical significance.



Computerised monitoring in neonatal intensive care. Typically a set of around ten measurements are taken once per second.

Model description



The FSKF model applied to physiological condition monitoring.

We use a Factorial Switching Kalman Filter (FSKF) to model the physiological data. This consists of three sets of variables which we call *factors*, *state* and *observations*. The hidden factors are discrete variables and model for example if the baby is in a normal respiratory state or not, or if a probe is disconnected or not. The state of baby $\mathbf{x}_t$ denotes continuous-valued quantities; this models the true values of infant's physiological variables, but also has dimensions to model certain artifact processes. The observations $\mathbf{y}_t$ are the noisy readings obtained from the monitoring equipment. For a given setting of the factors (a cross-product indexed by s_t), the hidden continuous state and the observations are related by:

$$\mathbf{x}_t \sim \mathcal{N}\left(\mathbf{A}^{(s_t)}\mathbf{x}_{t-1} + \mathbf{d}^{(s_t)}, \mathbf{Q}^{(s_t)}\right), \quad (1)$$

$$\mathbf{y}_t \sim \mathcal{N}\left(\mathbf{H}^{(s_t)}\mathbf{x}_t, \mathbf{R}^{(s_t)}\right). \quad (2)$$

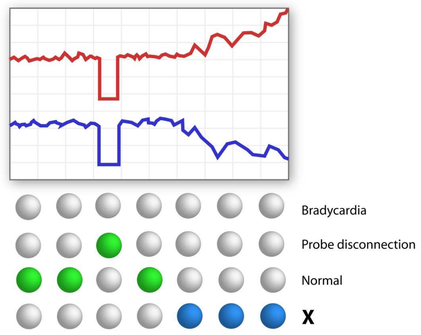
With labelled training data, the dynamics for each regime can therefore be trained as a Kalman filter with standard techniques.

Inference

Exact inference of the filtering distribution $p(s_t, \mathbf{x}_t|\mathbf{y}_{1:t})$ for the FSKF is intractable. Inference can be made possible with an analytical approximation (such as a Gaussian sum approximation) or with Monte Carlo methods (such as Rao-Blackwellised particle filtering).

Unusual dynamics

Another factor (referred to as the 'X-factor') can be added to the model, representing 'none of the above'. That is, it represents the periods in which the variation is not normal and none of the known factors. This is done by starting with a model for normal variation and inflating $\mathbf{Q}$ in (1).

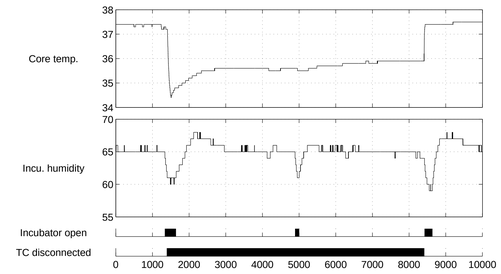


Operation of the X-factor. Lights represent which factors are active; green is used where there is a known interpretation, blue for the X-factor (where 'something else' is happening).

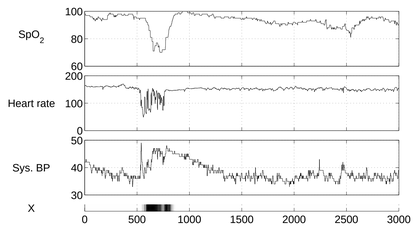
When the X-factor has the best predictive distribution of future values, we can infer that something is happening which has not been explicitly represented in our statistical model.

Results

Examples of the operation of the model are shown below. The horizontal axes show times in seconds.



Inferences of times the incubator was opened and the core temperature probe was disconnected.



A period of physiological instability being picked up by the X-factor.

Quantitative results for five known patterns are shown in the following table. GS denotes inference using the Gaussian sum approximation, RBPF denotes Rao-Blackwellised particle filtering. A baseline for performance is given by the factorial hidden Markov model (FHMM).

	Blood sample		TCP recal.		Bradycardia		TC disconnect		Incu. open	
	AUC	EER	AUC	EER	AUC	EER	AUC	EER	AUC	EER
FHMM	0.97	0.02	0.78	0.25	0.67	0.42	0.75	0.35	0.97	0.07
GS	**0.99**	**0.01**	**0.91**	**0.12**	0.72	0.39	**0.88**	**0.19**	**0.97**	**0.06**
RBPF	0.62	0.46	0.90	0.14	**0.76**	**0.37**	0.85	0.32	0.95	0.08

References

[1] C.K.I. Williams, J. Quinn, and N. McIntosh. Factorial Switching Kalman Filters for Condition Monitoring in Neonatal Intensive Care. In Y. Weiss, B. Schölkopf, and J. Platt, editors, *Advances in Neural Information Processing Systems 18*. MIT Press, 2006.