Individualised Optimisation of Modelled Cerebral Oxygenation Near-Infrared Spectroscopy Signals

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Motivation

Abstract: Responses of NIRS signals in a healthy volunteer are predicted using a model of brain circulation. Optimisation using partial data is shown to increase the model's predictive power which can aid the interpretation of NIRS signals in individuals.

- Noninvasive measurements of cerebral circulation and metabolism have the potential to significantly increase our understanding of the healthy and injured brain.
- The interpretation of near-infrared spectroscopy (NIRS) and other measured signals requires understanding not only of the physics of the measurement process, but also the underlying physiology.
- This leads to the use of methodologies where modelling, of physiology and the measurement process, play a key role.
- To be of use in a clinical context a model must be able to give insight not only into averaged behaviour of the signals, but also the behaviour of individuals.
- Given prior information/data for an individual subject-specific reparametrisation of the model may improve its ability to reproduce NIRS data for that individual.

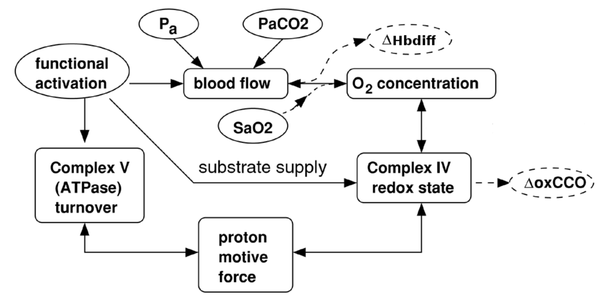
Methodology

- Brain tissue haemodynamics were monitored using a continuous wave NIRS broadband spectrometer developed in-house.
- Heart rate, mean arterial blood pressure (P_a), inspired oxygen concentration (FiO_2) and arterial oxygen saturation (SaO_2) were measured continuously.
- The first five minutes of the study monitored the subject at normoxia, after which nitrogen was added to the inspired gases until SaO_2 fell to 80%, at which point FiO_2 was returned to normal for a further five minutes. This procedure was repeated three times and the data divided into three challenges.
- The previously developed model of brain circulation and metabolism, BrainSignals, was constructed to aid interpretation of measured signals (such as those described above).
- Parameters which were either expected to have large physiological variation between individuals or can be hard to measure have been given "typical" values in the model. Hence, optimising these parameters is a natural progression in developing the use of the model.

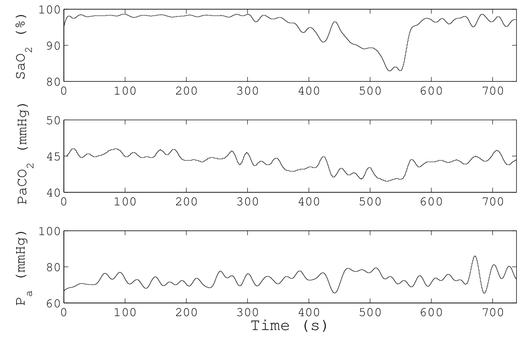
Model Optimisation

- For each of the three challenges, an optimisation was carried out.
- Parameters optimised were (all others were fixed at default values):
  - The normal venous-arterial volume ratio;
  - Blood concentration of haemoglobin;
  - A typical arteriolar radius;
  - A dimensionless parameter representing normal energy demand;
  - The strength of cerebral blood flow regulation in response to arterial O_2 levels;
  - The strength of cerebral blood flow regulation in response to changes in blood pressure;
  - The typical time-constant for the pressure autoregulation response.
- The optimisation of one challenge was then used to predict the behaviour of the other challenges.
- Prediction factors were used to give the average percentage improvement obtained from using each optimisation to predict the remaining unseen challenges.

The BrainSignals Model



(a) Model inputs are enclosed in solid ovals, while outputs of NIRS measured signals are enclosed in dashed ovals



(b) Input signals for a single challenge

FIGURE 1: Summary of the main inputs, variables and processes in the model used in this study.

- Inputs to the BrainSignals model were three measured systemic signals: mean P_a, SaO_2 and $EtCO_2$ (which was assumed to be equal to arterial partial pressure of CO_2, a model input parameter).
- The signals used to provide comparison between the modelled and measured data were the NIRS signals derived from the difference in the changes in tissue oxy- and deoxy-haemoglobin concentrations ΔHbdiff.
- The unweighted mean distance between measured and modelled values of ΔHbdiff during the challenge gives a quantifiable measure of the success of the model at reproducing the signals.
- In addition to the haemoglobin chromophores, changes in oxidation state of the Cu_A centre in cytochrome *c* oxidase (ΔoxCCO) known to be a significant NIR absorber were measured.

References

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Results

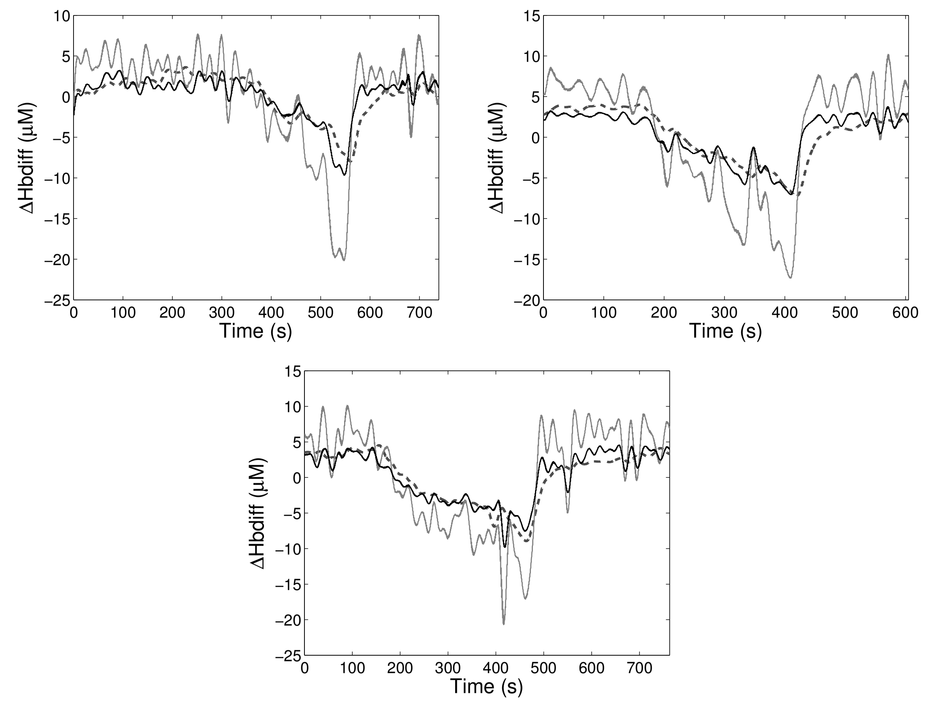

FIGURE 2: Modelled and measured ΔHbdiff signals during hypoxic challenges. Bold lines are the optimised model output, grey lines the unoptimised model while the dashed lines are measured data.

TABLE 1: Signal-to-data distances and prediction factors for each challenge and the average for all three challenges.

ΔHbdiff	Challenge 1	Challenge 2	Challenge 3	Average
Unoptimised distances	0.853	0.983	0.889	0.908
Optimised distances	0.273	0.260	0.250	0.261
Prediction factors	66.94%	71.01%	62.08%	66.67%
ΔoxCCO				
Unoptimised distances	0.254	0.224	0.233	0.237
Optimised distances	0.215	0.194	0.205	0.205
Prediction factors	7.87%	3.57%	-2.58%	2.96%

- The average weighted distance between modelled and measured ΔHbdiff was improved by 71.26% and there is a considerable improvement in the prediction following individualisation.
- The distances between the unoptimised model and the measured data for ΔoxCCO for all three challenges are small and the improvement post optimisation averaged 13.64%, while on average the prediction factors show a small improvement, for challenge 3 when optimising the model on data from the other challenges results in a small decrease in predictive accuracy.

Conclusions

- Interpretation of optical measurements is key to their use in clinical applications, from the preliminary results presented in this work it can be seen that there is scope for modelling in the interpretation of NIRS signals
- Individualisation of the model can improve the predictive performance of the model, loosely speaking, knowledge of the NIRS data during one challenge improves the ability of the model to predict the behaviour of NIRS signals in subsequent challenges.
- A mismatch between modelled and measured values of ΔHbdiff may be at least partly attributable to the choice of model parameters. However, for the ΔoxCCO signals the unoptimised model could reasonably reproduce the measured signals and optimisation did not greatly reduce the model-to-data distance.

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