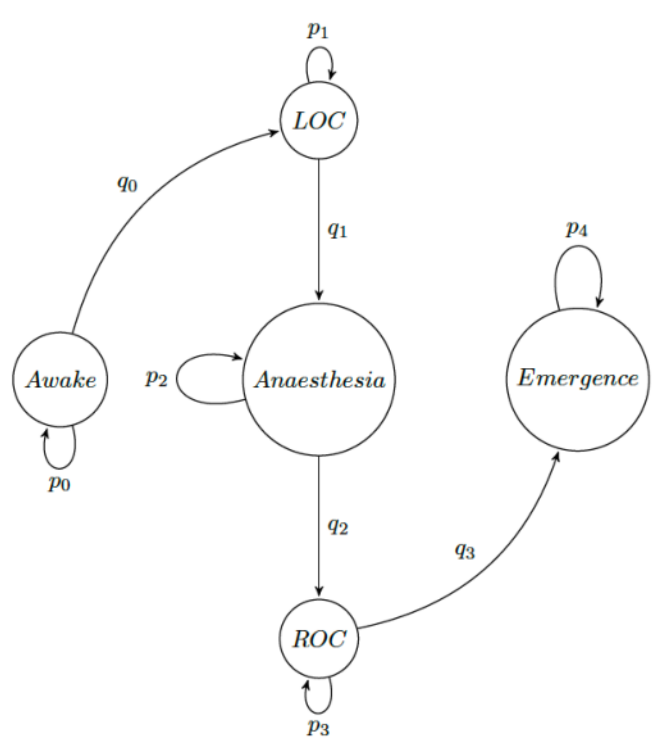
Longitudinal individual follow-up of physiological variables during general anesthesia: development of a mathematical signature of general anesthesia

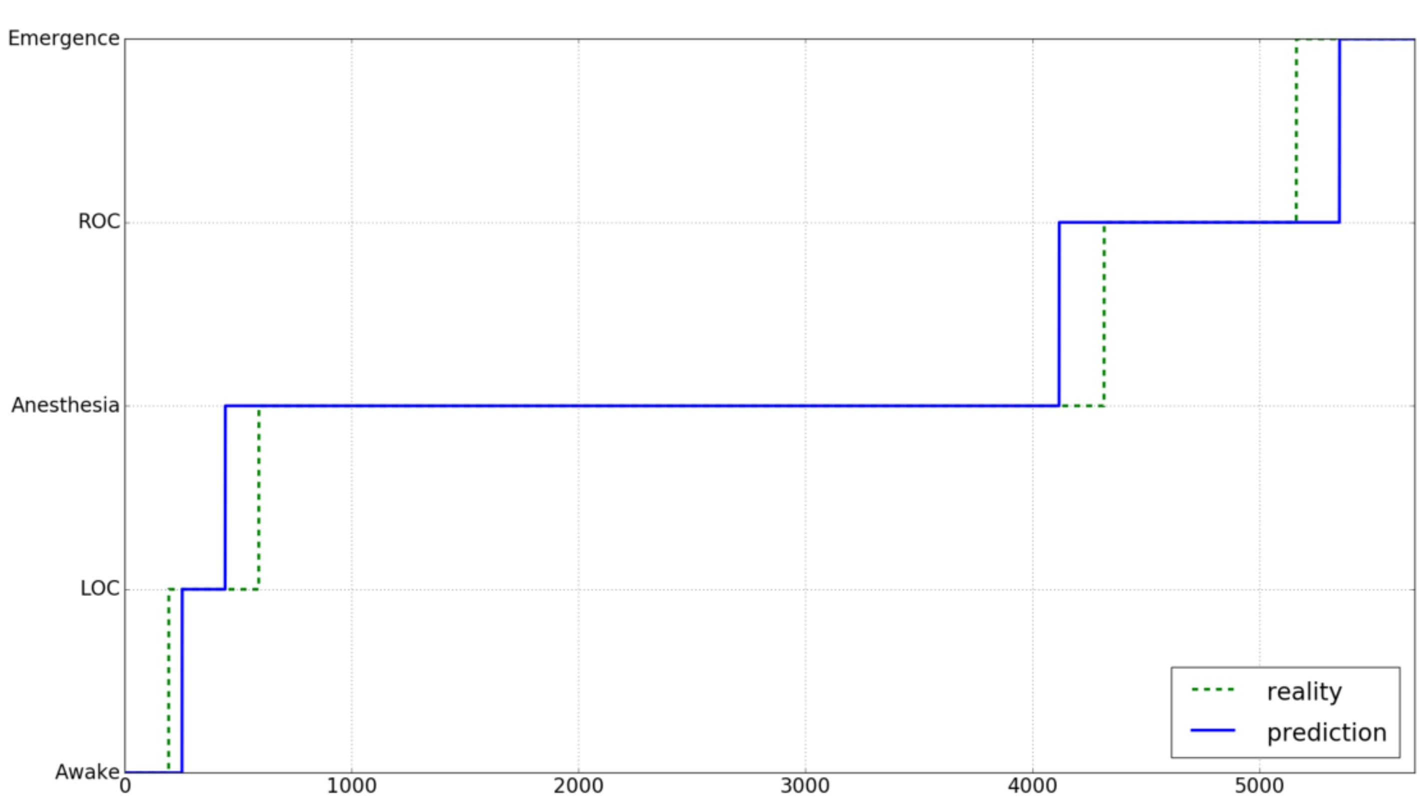
Dubost C.[1,2], Humbert P.[1,3], Oudre L.[1,3], Buffat S.[1], Ould-Ahmed M.[2], Vayatis N.[1,3], Vidal P.-P.[1]

1: CognacG Research Lab, Univ Paris-Descartes-CNRS-SSA, 2: Dept of Anaesthesiology & Intensive Care, Begin Military Hospital, Saint-Mande, France, 3: CMLA, Mathematics Lab, Cachan, France

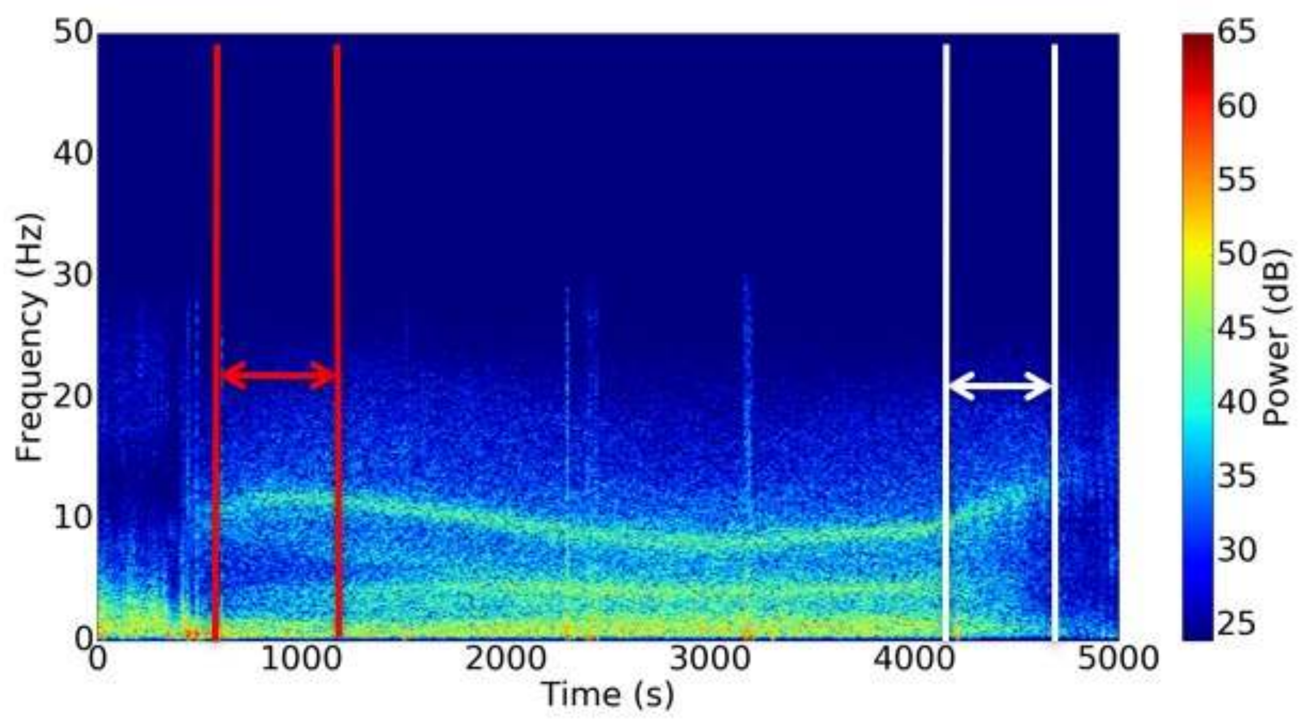
Background and Goal of Study: Precise identification of the depth of anesthesia remains an unmet need in anesthesia. The gold-standard for depth of anesthesia is the electroencephalogram (EEG), which is not realistic for all the patients in the daily routine. Thanks to multimodal monitoring, we aimed at developing a mathematical signature of the anesthesia, which will then allow the development of a predictive model of consciousness.

Materials and Methods: The monitoring included electrocardiogram (EKG), pulse oxymetry, non-invasive blood pressure, gas analysis and plethysmography. The 2-channel EEG was recorded at 100 Hz, EKG at 300 Hz and all the other variables at 1 Hz. The 5 more clinically relevant variables were included in the first model: Heart Rate, mean BP, Respiratory Rate, AA_FI & O_2_FI. In order to perform machine learning, we standardized the data. Variables were then analyzed with a Hidden Markov Model.





Measures	values
Age, yr	60 (24, 92)
Sex, F/M	20/10
Weight, kg	82 (50, 105)
Height, cm	176 (159, 191)
ASA I/II	12/18



Results and Discussion: The development of a free software allowed proper and stable recording of the desired variables (VSCapture, Karippacheril JG©).

Thirty patients were included and demonstrated high quality signal throughout the recording. Objective identification of the 5 states of interest: Awake, Loss of Consciousness (LOC), Anesthesia, Recovery of Consciousness (ROC) and Emergence were possible on the EEG of 16 patients. Each variable was divided into 5 classes. The model was trained on 80% of the sample and validated on the whole sample.

The mean latency to detect transition to the next stage was:

	LOC	Anesthesia	ROC	Emergence
Latency (s.)	60	21	72	37

The percentage of error for the prediction was 18%.

The good predictability obtained by our algorithm must be interpreted cautiously as only 16 patients were included. Transition states (i.e. LOC & ROC) are not easy to detect and may not always be as sharp as they have been labelled when training the algorithm.

The next step for our work will be to test this algorithm on more patients and check its robustness.

Conclusion: In this work, we presented a simple model to encode the anesthesia process. We then learned a policy on this model, using expert trajectories. The performances of the resulting policy results look promising, and future research directions might include the creation of a more complex model, where inverse reinforcement learning could be used.

clement.dubost@hotmail.fr