Intelligent Fuzzy Computing for Biomedical Signal Analysis

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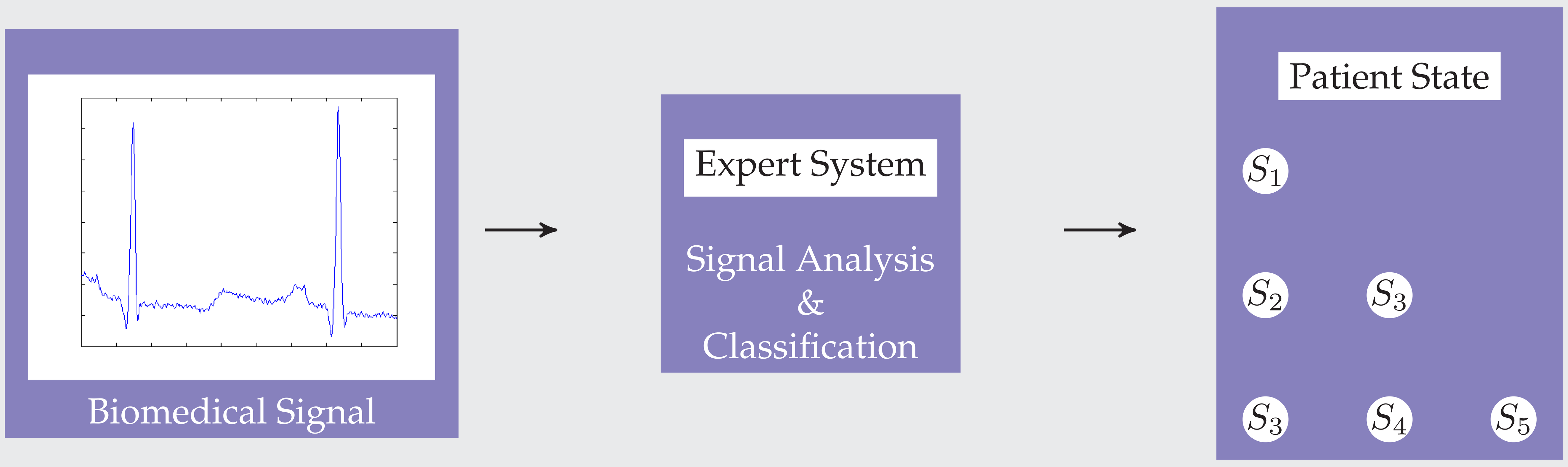
The Problem: Physiological Signal to Individual Assessment

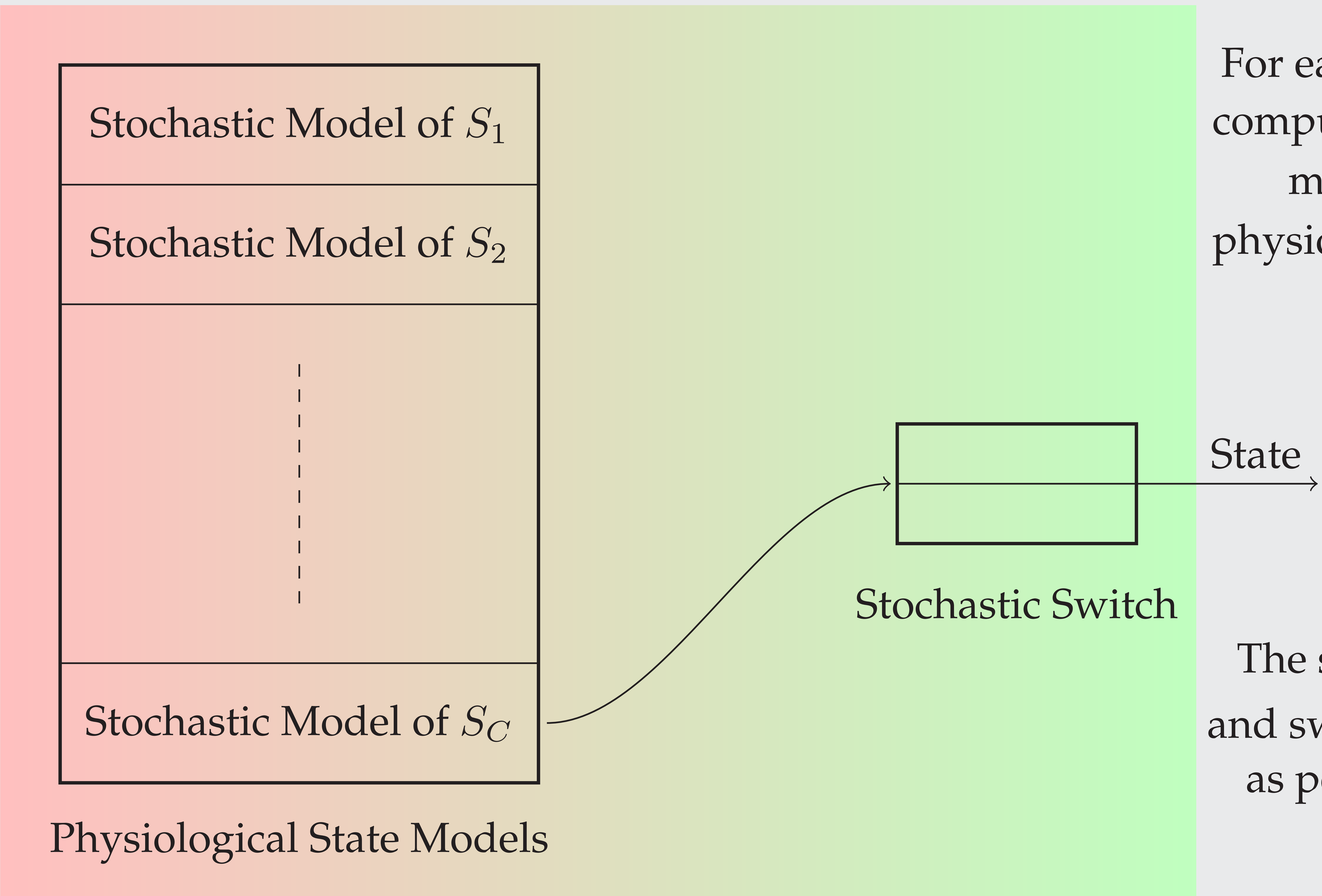


- Extraction of relevant signal features and mapping features to the states.

The Difficulties

- The physiological signals are typically contaminated with noise and artifacts.
- The signal features based on the typical statistical, spectral, non-linear dynamical, and adaptive modeling analysis might not be enough diagnostic efficient in distinguishing the patients' physiological states.
- The uncertain and complex relationships between physiological states and physiological signals are difficult to be modeled using classical modeling approaches.

Approach: Computational Intelligence based Stochastic Analysis

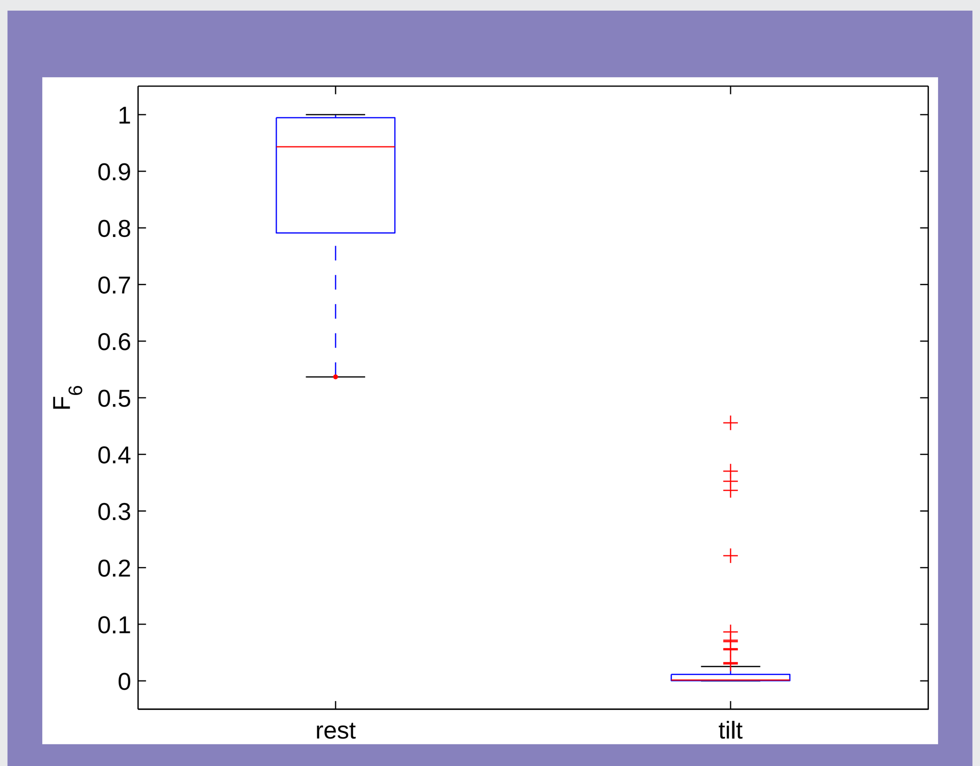


For each of the states, we have a computational intelligence based model characterizing the physiological state of the patient.

The switch analyzes the signal and switches between the models as per the physiological state.

Tilt-table Experiment

- The participants (N = 40) lay supine on the tilting table for 10 minutes followed by a 10 minutes head-up tilt at 70°.
- The physiological response of the subjects was assessed via measuring their heartbeat intervals.
- It was possible to predict accurately the either state via calculating the state probabilities.



State Classification

Stochastic Fuzzy Modeling of Physiological States

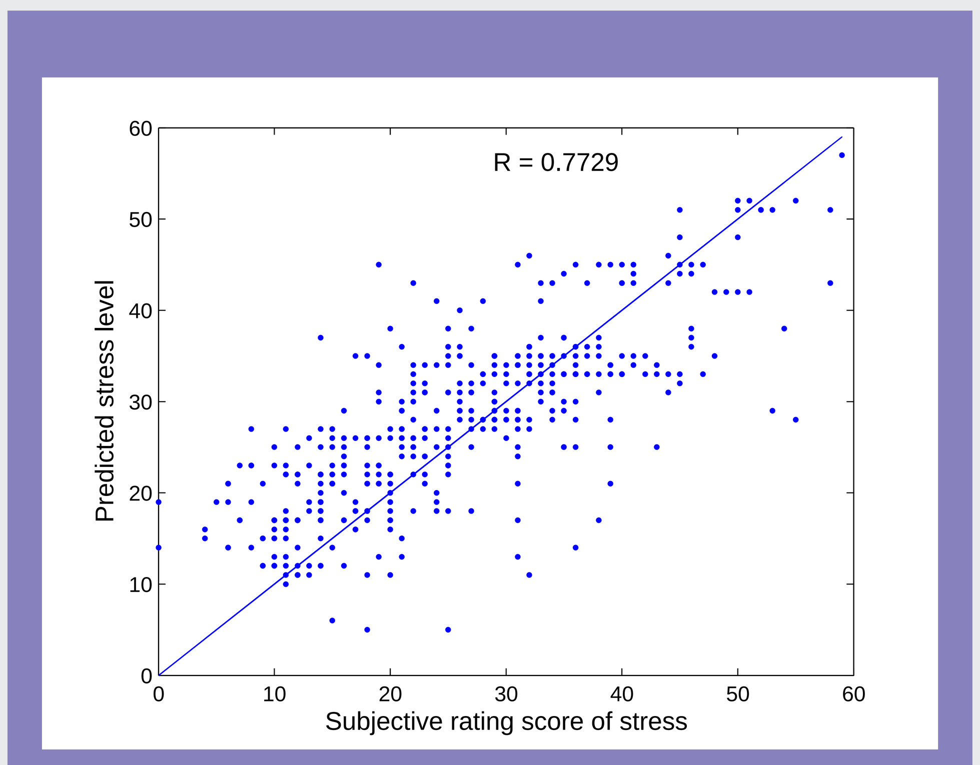
- The signal of a patient P with physiological state S is modeled as a history-dependent probability density:

$$
\begin{aligned}
\mathfrak{M}: \quad p\left(y_j | y_{j-1}, y_{j-2}, \cdots, y_{j-n}\right) &\propto e^{-\dfrac{\phi|y_j - FM\left(y_{j-1}, y_{j-2}, \cdots, y_{j-n}; \alpha\right)|^2}{2}} \\
p(\alpha | m_0, \Lambda_0) &= N(\alpha | m_0, (\Lambda_0)^{-1}) \\
p(\phi | a_0, b_0) &= \frac{1}{\Gamma(b_0)} \frac{\phi^{b_0 - 1}}{a_0^{b_0}} e^{-\dfrac{\phi}{a_0}}, \ \phi > 0, a_0, b_0 > 0.
\end{aligned}
$$

- Bayesian inference of the nonlinear fuzzy physiological state model $\mathfrak{m}$ is the first goal of the method.

Stress Assessment Applications

- Stress monitoring for mobile telemedical applications.
- N = 50, 24-hours stress monitoring, prediction accuracy $R = 0.7729$.



Stress Prediction Accuracy

Physiological State Prediction

- A discrete random variable s is introduced such that the value of s reflects that $s-$th physiological model might have generated the current physiological signal. That is,

$$
\begin{gathered}
\text{If random variable } s = 1\text{, then signal is generated by model } \mathfrak{M}_1 \\
\vdots \\
\text{If random variable } s = C\text{, then signal is generated by model } \mathfrak{M}_C
\end{gathered}
$$

- Let $\pi = [\pi_1 \cdots \pi_S]^T \in R^S$ be the vector of probabilities such that

$$p(s = 1|\pi) = \pi_1, \cdots, p(s = C|\pi) = \pi_C$$

where π is generated by a Dirichlet distribution:

$$p(\pi | c_0) = \frac{\Gamma(c_0)}{(\Gamma(\frac{c_0}{S}))^S} \pi_1^{\dfrac{c_0}{S} - 1} \cdots \pi_S^{\dfrac{c_0}{S} - 1}, \ \pi_1, \cdots, \pi_S \geq 0, \ \sum_{j=1}^{S} \pi_j = 1, \ c_0 > 0.$$

Conclusion

- The intelligent fuzzy computing based biomedical signal analysis methods possess a high diagnostic efficiency and thus the physiological states of the subjects could be accurately predicted.