SUBJECT: Information Theory and Machine Learning based approach for effective biomedical signal Classification and Feature extraction

SUPERVISOR:

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Name of the institute in which the topic will be realized: Institute of Fundamental Technological Research
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PROJECT DESCRIPTION

Currently, substantial efforts are being developed for the enrichment of medical imaging applications using these algorithms to diagnose the errors in disease diagnostic systems which may result in extremely ambiguous medical treatments [1]. Biomedical signals (EEG, EKG, MEG, MRI, etc.) can be analyzed in several ways using different mathematical theories and tools (Statistical analysis, Fourier analysis, Wavelet analysis). Recently, Information Theory is strongly exploited. Concepts derived from Information Theory such as entropy, discrete entropy, Renyi entropy, permutation entropy, mutual information, complexity, permutation complexity, and discrete Lyapunov exponents allow us a deeper insight into the nature of biosignals. This is because they take into account simultaneously the probabilistic nature and the structures of signals (e.g. internal patterns of signals [2–5]). Besides, these techniques have a unique feature that enables measuring the level of randomness of signals and distinguishing deterministic traits from random features. This is extremely important in the classification of such complex signals as the ECG, EEG, MEG, and MRI especially in the early stages of anomaly formation when detection of subtle differences is crucial [6, 7]. Based on our previous information-theoretic research [8, 9] we set the following research hypothesis that Information Theory can be successfully applied as a clinical tool for vital signs abnormalities classification. Before applying the Information Theory-based tools, biosignals have to be converted into a discrete sequence of symbols. It is known that the effectiveness of the signals classifications method strongly depends on the signal digitalization applied [10, 11]. Codification (digitalization) can take place in various ways. A successful encoding method of biomedical signals (e.g. a sequence of measurements performed with some sampling frequency) into sequences of symbols from a given finite alphabet is one of the important issues. Specifically, in choosing a biosignal digitization method, the challenge is also to adopt the most effective parameters, and here the use of the Machine Learning approach is the most promising idea.

The Doctoral Thesis aims to develop and implement **new effective classification algorithms based on Information Theory concepts and** support these algorithms with **Machine Learning techniques**. Such algorithms should allow to **analysis and classification effectively biomedical signals online**. This software will be responsible for analyzing patient data from an electrocardiogram, heartbeat sensor, and other relevant medical data, classifying subjects' exam results, and providing a suggestion about his/her health status.

Diagnostics algorithms will be validated on:

- simulated signals modeling experimental recordings and on the *in vivo* recordings, e.g. electrical heart activity and brain signals (individual sensory neurons) and

- on signals coming from an experimental database of *Mount Sinai Hospital New York, USA, IDIBAPS Institut d'investigacions Biomèdiques August Pi i Sunyer Barcelona, Spain,* and *Peacs BV Netherland*.

The results obtained will support **intelligent monitoring of patients** and help deliver **targeted**, **and personalized medicine** while providing smooth communication and high productivity in medical units.

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