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Editorial

Special Issue: "Research on Biomedical Signal Processing"

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Over recent years, the number of signals of a different type that can be acquired from the human body has increased extraordinarily. In addition, the power of digital electronic devices has exploded, making it possible to manage a complex multi-signal environment capable of estimating multivariate time-variant models in real time. Finally, advances in machine learning (ML) theory and the increased availability of large signal databases make the application of deep learning feasible. We believe that the sum of these advancements produces significant achievements in biomedical signal processing, supporting accurate diagnosis and efficient medical decision making.

This Special Issue is intended to provide the reader with a collection of research articles that represent examples of a wide and varied array of signals and methods of analysis.

With the development of wearable biomedical sensors, the number and duration of biomedical signals have increased significantly, but random noise and external interference affect most of them. Therefore, signal processing techniques have been applied to cancel artifacts and reduce noise, increasing the signal quality for subsequent analysis. The multisignal framework has been used to develop new artifact removal methods. One such methods is artifact subspace reconstruction (ASR). To this end, the paper of Plechawska-Wójcik et al. [1] evaluated the influence of ASR on EEG signals.

The paper of Bachi et al. [2] presented a high-computational-efficiency algorithm for QRS complex detection that had been specifically designed for ECG analysis in wearable devices.

Ferdinando et al., in their paper [3], proposed continuous human cardiac monitoring by analyzing signals from accelerometers placed on the chest.

De La Pava Panche et al. [4] estimated directed phase–amplitude interactions from EEG data through kernel-based phase transfer entropy. Cross-frequency interactions, a form of oscillatory neural activity, are thought to play an essential role in the integration of distributed information in the brain. Indeed, phase–amplitude interactions are believed to allow for the transfer of information from large-scale brain networks oscillating at low frequencies, to local, rapidly oscillating neural assemblies.

Functional near-infrared spectroscopy (fNIRS) is an attractive technology, especially in the field of neuroscience, on account of its non-invasiveness, portability, cost-effectiveness and long-term monitoring capability. However, to date, fNIRS has found limited clinical use due to poor spatial resolution, shallow penetration depth, lack of anatomical specificity and low within-subject reproducibility.

Current fNIRS instrumentation provides nonstandard outputs, and objective standardization of preprocessing and analysis pipelines is required to construct homogeneous and standardized databases for application to clinical research. The paper authored by Bonilauri et al. [5] addressed this issue.

Paternoster and Seiberl [6] compared five different approaches in estimating skeletal muscle oxygen consumption using continuous-wave near-infrared Spectroscopy (CW-NIRS). Repeated-measures ANOVA have identified significant differences among the five oxygen consumption estimates, meaning that studies using different approaches are not directly comparable.

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In recent years, the scientific community has developed technologies for constructing exoskeletal devices or prostheses to compensate for the motor deficits of people with disabilities. The interfaces for controlling such robotic devices are mostly based on non-invasive electromyographic (EMG) signaling. He et al. [7] proposed a musculoskeletal model based on muscle synergy for the continuous estimation of hand and wrist motion. To separate specific deep-muscle activation, the signals were analyzed using independent component analysis (ICA) and non-negative matrix decomposition (NMF) was then applied to extract muscle synergies.

Zuccalà et al. [8] reported on the use of some of the features extracted from physiological signals (including heart rate, heart rate variability, respiratory rate, galvanic skin response) to recognize stress in response to moderate cognitive activation in daily-life settings. The relevance of the various features was investigated using two approaches: sequential forward feature selection (SFFS) and auto-encoder (AE) neural networks. The self-organizing map (SOM) method was used to provide a flexible representation of an individual's status. Vaz et al. [9] addressed the problem of predicting anxiety levels from physiological signals collected without any emotional elicitation. Electrocardiogram (ECG), electrodermal activity (EDA), and electromyogram (EMG) signals were considered. Features extracted from the ECG were found to be the most relevant for anxiety classification. Aresta et al. [10] combined biomechanical features and ML approaches to identify fencers' levels. In order to determine the best classifier for the novice or élite athlete class, four supervised models (extreme gradient boosting; multilayer perceptron (MLP); random forest; support vector machine) were trained and tested on biomechanical data. The MLP results identified it as the best model.

This Special Issue also includes two reviews. The first (Park and Kim [11]) concerns the application of ML in the field of intraoperative neurophysiological monitoring (IONM) as a diagnostic tool for the protection of patients from neural injury that may occur during surgery, improving patient safety and minimizing neurological damage. Although the application of ML to IONM remains limited, such an approach enables clinicians to perform objective and reliable IONM.

The second review (Kumar and Ramachandran [12]) provides a comprehensive evaluation of compressive sensing (CS) research in biosignal compression, particularly in one-dimensional ECG. In recent years, home patient monitoring devices have become more and more common, something that has also required the acquisition and transmission of larger amounts of biomedical data and signals to the care center server for remote analysis. This has resulted in huge data flows, making it pivotal to reduce such flows while maintaining high accuracy of information.

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