Abstract

This doctoral dissertation presents a series of five articles focused on the verification of the potential application of cardiorespiratory signal analysis, extended with causal and informational domains, to improve health status assessment. In the first step, an analysis based on 369 cardiopulmonary exercise test recordings was conducted to predict VO_{2peak} values with various sets of cardiorespiratory parameters. The obtained results indicated a statistically significant improvement in prediction quality when respiratory parameters were included alongside cardiac parameters, achieving the lowest mean absolute percentage error of 10.51%. Subsequently, the *nonlincausality* package, developed in Python for causality analysis using machine learning models, was introduced. This tool enabled the parameterization of nonlinear causal relationships that were undetectable using the classical Granger method. Next, the possibility of applying the developed package and other available causality analysis techniques to cardiorespiratory signals in a group of 20 pediatric cardiac patients was tested, with each method successfully identifying and numerically quantifying the interdependence between cardiovascular and respiratory system activity. Another study presented the pilot use of an extensive set of features describing cardiovascular activity, respiratory parameters, and features from causal and informational domains combined with machine learning methods to predict the duration of a cardiopulmonary exercise test based on 5-minute static measurements in a lying position in a group of 36 young soccer players. The obtained results were characterized by moderate accuracy, with a mean absolute percentage error of 17.1% and a mean absolute error of 129 seconds. Explainable artificial intelligence techniques provided insight into the influence of individual features on the model's outcomes, highlighting the critical importance of cardiac parameters while emphasizing the need to include information from respiratory signals and cardiorespiratory interdependencies. The final publication described the use of machine learning techniques to classify an individual's health status based on cardiorespiratory parameters, including those from causal and informational domains. This study involved 135 participants aged between 6 and 17 years, each assigned to one of three groups depending on their health status. For a dataset comprising the 35 most significant parameters, an accuracy of 89.1% was achieved. The results showed a statistically significant improvement in classification quality for datasets containing parameters from causal and informational domains, indicating their possibly valuable diagnostic information. The conducted analyses demonstrate the practical potential of utilizing the presented methods and tools in medical diagnostics. The application of cardiorespiratory parameters, including features from causal and informational domains, could enable more precise health monitoring, training progress evaluation, and the personalization of healthcare.

Keywords: Cardiorespiratory coupling, causal analysis, machine learning, cardiorespiratory parameters, impedance pneumography