PHYSIOLOGICAL META-INDICATORS FOR PROFESSIONAL SPORTS APPLICATIONS: EXPRESS DIAGNOSTICS, OVERTRAINING DETECTION, AND QUANTIFICATION OF INDIVIDUAL ZONES OF OPTIMAL FUNCTIONING.

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Importance of systematic and objective psycho-physiological monitoring of athletes in professional sport constantly increases. Express medical diagnostics of emerging cardiac abnormalities, early detection of overtraining and similar negative changes in psycho-physiological state of athletes critically depend on the quality of such monitoring. Related challenging problem without existing universal solution is robust identification of the individual zones of optimal functioning (IZOF) [1]. Tuning an athlete into his/her own IZOF could dramatically improve stability of his/her performance and increase probability of the highest achievements. However, it is difficult to quantify such optimal zones.

Technological advancements in portable and wearable systems for real-time collection of physiological data provide new opportunities for computerized diagnostics and quantitative modeling not only in medicine, but also for related applications in sports industry. For example, modern sport watches with ECG-type sensors can be used not only for programming personalized training sessions but also for simultaneous collection of beat-to-beat (RR) time series with accuracy comparable to clinical ECG equipment [2]. Such personal RR data can be used for systematic heart rate variability (HRV) analysis [3] to provide early indication of developing cardiac abnormalities, overtraining detection and for other purposes. However, many algorithmic and modeling challenges in such applications remain unresolved, especially for applications where short time series are used. These include instability of pure statistical and machine learning models due to non-stationarity, noise, and data incompleteness as well as ambiguity of the existing analytical indicators.

Recently, we have demonstrated that many of these challenges could be overcome by combining complementary HRV indicators using boosting-like ensemble learning methods [4-6]. It is possible to discover multi-component meta-models with acceptable accuracy and stability even when short time series (~ several minutes) are used. For example, we have shown that application of boosting can significantly increase detection rate of such abnormalities as congestive heart failure (CHF), different types of arrhythmia, paroxysmal atrial fibrillation (PAF), and their combinations [4-6]. These meta-indicators could be very useful for express diagnostics of athletes from short segments of RR data. For example, hypertrophic cardiomyopathy (HCM) is hard-to-detect cardiac disease that is a leading cause of sudden death in young athletes [7]. Although different in nature, HCM shares common diagnostics features with CHF and is often accompanied by arrhythmias [7]. Therefore, indicators capable of robust detection of CHF and arrhythmias may provide early warning signs of developing HCM.

Probability-like aggregated output and internal structure of such multi-component indicators could also be used for the more subtle quantification of psycho-physiological states. For example, HRV-based indicators may offer fast and convenient detection of overtraining [8]. This approach could provide an alternative for much less convenient and time-consuming psycho-physiological evaluations of overtraining currently adopted. However, individual HRV measures could often produce ambiguous results in practice [8]. In contrast, quantification based on our meta-indicators could offer much more stable and practical solution. Moreover, our framework can be also used for detection and quantification of optimal psycho-physiological states. The concept of IZOF introduced in sport psychology revealed multi-featured (multi-dimensional) nature of personal psycho-physiological states associated with the best performance [1]. Therefore, while it is difficult to quantify such optimal zones using existing approaches, multi-component representation offered by our framework could be well-suited for this task.

Multi-objective performance metrics of our physiological meta-indicators calculated from normal/abnormal data taken from www.physionet.org will be presented. Operational details of application of such meta-indicators in professional sports ranging from personal psycho-physiological diagnostics to optimization of team-selection strategies will be discussed. Multi-component decision-support system for coaches and athletes will be also outlined.

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