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Human fatigue assessment method based on plantar pressure distribution and limb movement monitoring

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Although fatigue is a subjective sensation, objective physiological indicators can provide quantitative criteria. Fatigue impairs an athlete's ability to sustain prescribed exercise intensity, reduces responsiveness, and significantly diminishes training efficiency and effectiveness. If not addressed promptly, fatigue may accumulate and lead to overexertion [1], increasing the risk of tendonitis, lumbar strain, stress fractures, and other sports-related injuries. Therefore, routine monitoring and quantitative assessment of exercise-induced fatigue are essential. Timely alerts facilitate physiological recovery, thereby improving training outcomes and minimizing injury risk.

Fatigue assessment can be performed using subjective and objective approaches. Subjective methods, which are often based on questionnaires, are convenient but suffer from high subjectivity and limited accuracy. In contrast, objective methods rely on monitoring biochemical or physiological signals. A growing body of research supports the correlation between physiological indicators and fatigue levels. For instance, Umer et al. developed a fatigue assessment model based on cardiorespiratory and temperature parameters and confirmed their association with fatigue [2]. Similarly, Hamzavi et al. examined the effects of fatigue on plantar pressure across different runner types and demonstrated a significant link between fatigue and patterns [3]. However, conventional objective monitoring techniques are predominantly invasive and have notable limitations, such as high costs, bulky equipment unsuitable for dynamic testing, and a lack of real-time feedback, all of which hinder their widespread implementation.

In recent years, wearable systems have emerged as promising alternatives for fatigue monitoring. Flexible sensors offer advantages such as lightweight design, compact size, and adaptability across various settings, thereby opening new fatigue assessment opportunities. For instance, Song et al. used a hip angle sensor to monitor changes in hip angle during walking, determining fatigue levels based on the percentage of maximum oxygen uptake [4]. Torres et al. employed accelerometers and used a support vector machine (SVM) classifier to discriminate between normal and fatigued gait patterns, achieving a prediction accuracy of 90% [5]. However, most existing fatigue monitoring systems rely on a single physiological signal, which limits the comprehensiveness and accuracy of fatigue assessments.

To overcome these limitations, we propose a novel fatigue assessment method based on plantar pressure distribution and limb movement monitoring. This approach enables real-time, dynamic tracking of human motion and comprehensive fatigue quantification through multidimensional data analysis. A noninvasive evaluation system was developed by integrating an inertial measurement unit (IMU) with a custom-designed smart insole. By applying statistical modeling and machine learning algorithms to analyze physiological data at varying fatigue levels and by integrating multisource feature information, we successfully identified 19 distinct exercise states. In addition, we established a two-level walking fatigue model and a four-level running fatigue model, both of which achieved prediction accuracies exceeding 98%. This method not only supports timely adjustments of exercise intensity, thereby optimizing training efficiency and reducing fatigue-related injury risk, but also shows strong potential for application in athlete training support, routine physical monitoring, and medical rehabilitation.

Overview of the noninvasive fatigue evaluation system. As illustrated in Figure 1(a), the system innovatively combines IMUs a custom-developed smart insoles, enabling synchronous capture of dynamic acceleration from the waist and ankle, as well as plantar pressure distribution data. Through the integration of wireless communication, multimodal signal processing, and machine learning algorithms, the system can efficiently analyze heterogeneous features from multiple sources to construct a fatigue prediction model with strong

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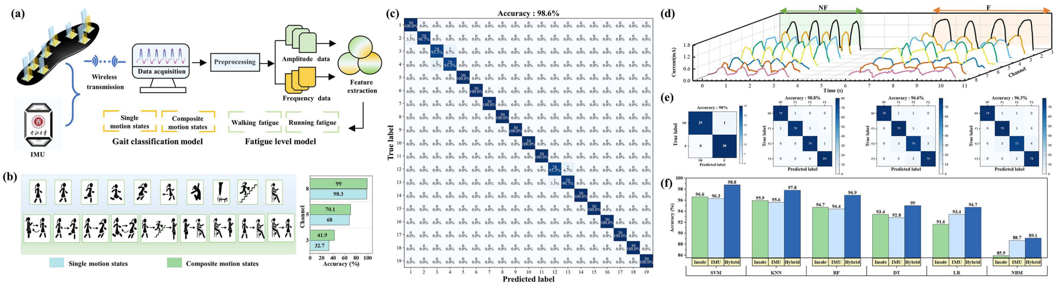

Figure 1 (Color online) (a) Schematic diagram of the technical framework for exercise fatigue monitoring; (b) human movement states to be recognized (01–10: single motion states; 11–19: composite motion states) and confusion matrices under varying channel counts; (c) confusion matrix of the 19 movement states using an 8-channel configuration; (d) electrical response of the smart insole during human walking under nonfatigue (NF) and fatigue (F) conditions; (e) confusion matrices for fatigue classification: two-level walking fatigue (leftmost) and four-level running fatigue across three sensor configurations (hybrid, insole only, IMU only, from left to right); (f) classification accuracies for running fatigue levels using six machine learning algorithms across the three sensor configurations.

generalization capability. This enables comprehensive, noninvasive, real-time monitoring and quantitative assessment of human fatigue. The smart insole features a miniaturized array design with eight embedded ultrathin, flexible piezoresistive sensor units (MMPS), allowing for comprehensive, nonintrusive monitoring of plantar pressure variations during movement. Additional technical specifications and design details are provided in Appendix A.

Recognition of human motion states. To accurately quantify exercise-induced fatigue, it is first essential to distinguish between single and composite motion states based on the short-term continuity characteristics of human movement. Accordingly, eight flexible sensing units were strategically deployed in high-pressure regions of the foot, such as the forefoot, lateral midfoot, and heel, forming a multichannel plantar sensing network within the smart insole. After data acquisition via Bluetooth, the signals undergo noise filtering, feature extraction in both the time and frequency domain, and central normalization. Principal component analysis (PCA) is then applied for feature dimensionality reduction. Experimental results indicate that the 8-channel configuration achieves a classification accuracy of 98.3% for single motion states and 99% for composite states. In mixed gaits conditions, the system accurately identifies all 19 defined motion states with an overall accuracy of 98.6% (Figures 1(b) and (c)). Further methodological details are available in Appendix B.

Human walking fatigue assessment system. We developed a two-level hierarchical model for the quantification of gait fatigue. By integrating time-domain dynamic features of plantar pressure with frequency-domain spectral characteristics and applying a K-nearest neighbor classification algorithm, we defined the first and last 20 s of each walking sequence as the nonfatigue (NF) reference state and the fatigue (F) critical state, respectively (Figures 1(d) and (e)). A two-phase feature space was then constructed to precisely model the progression of fatigue. Experimental results demonstrated a classification accuracy of 98.3%, with only one NF sample misclassified, likely due to individual gait variability. The model achieved an area under the curve value of 0.9, indicating high discriminative performance. Additional details are provided in Appendix C.

Human running fatigue assessment system. We propose a four-level quantitative fatigue assessment model for running, based on the synergistic analysis of gait dynamics and kinematic features using a smart insole-IMU multimodal sensor fusion system. The fatigue evolution process was simulated by a graded acceleration scheme, while real-time heart rate data were recorded with a Polar heart rate belt to validate fatigue level classification. The fatigue prediction model was constructed by extracting 102-dimensional feature vectors, calculating the time-frequency domain features based on the gait cycle segmentation method, and using a support vector machine (SVM) after normalisation and principal component analysis. Among 400 samples, the hybrid sensor SVM model achieved a classification accuracy of 98.8% (Figures 1(e) and (f)), significantly outperforming models based on single-sensor input. This highlights the effectiveness of multisource data fusion in enhancing assessment robustness. The method enables accurate graded early warning of fatigue, ranging from mild (F1: facial redness, reduced attention) to moderate (F2: palpitations, shortness of breath), and severe (F3: potential risk of irreversible injury), through noninvasive multimodal sensing and machine learning-based quantitative evaluation. This approach provides technical support for athletic health monitoring and rehabilitation intervention. Additional details are provided in Appendix D.

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Supporting information Appendixes A–D. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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