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INTEGRATION OF BIOPHYSICS AND INFORMATION TECHNOLOGIES FOR MODELING HUMAN BIOMECHANICAL MOVEMENTS USING 3D SENSORS AND MACHINE LEARNING

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Abstract

Human biomechanical movement analysis plays a crucial role in biophysics, rehabilitation medicine, sports science, and intelligent human-machine interaction systems. This study focuses on the integration of biophysics and information technologies for modeling human biomechanical movements, particularly gait and upper limb motions, using 3D sensor technologies and machine learning methods. Motion data were acquired using inertial measurement units (IMUs), optical motion capture systems, and depth sensors to record spatial-temporal kinematic parameters. Biophysical signal processing techniques, including noise filtering, drift compensation, and quaternion-based orientation reconstruction, were applied to ensure accurate motion representation. Extracted kinematic features such as joint angles, velocity, and acceleration were utilized to train machine learning models, including Random Forest, Long Short-Term Memory (LSTM) networks, and Transformer-based architectures. The results demonstrate that deep learning models effectively capture temporal dependencies in biomechanical signals, achieving high accuracy in movement classification and trajectory prediction. The proposed biophysics-IT integrated approach provides a robust framework for objective movement assessment and

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has significant potential applications in clinical rehabilitation, sports performance analysis, robotics, and intelligent biomedical systems.

Keywords. Biophysics integration, biomechanical movement analysis, 3D sensors, inertial measurement units, motion capture, machine learning, deep learning, gait analysis, human movement modeling.

Introduction

The analysis of human biomechanical movements is a fundamental research area at the intersection of biophysics, biomedical engineering, and information technologies. Human motion is governed by complex interactions between the musculoskeletal system, neural control mechanisms, and physical laws such as kinematics, dynamics, and energy conservation. Understanding these interactions is essential for objective assessment of movement efficiency, early diagnosis of motor disorders, rehabilitation monitoring, and the development of intelligent assistive and robotic systems.

From a biophysical perspective, human movement can be described through spatial-temporal parameters, joint kinematics, segmental dynamics, and force generation mechanisms. Traditional biomechanical analysis relies on laboratory-based measurements, force platforms, and optical motion capture systems, which provide high accuracy but are often expensive, stationary, and limited to controlled environments. These constraints reduce their applicability in long-term monitoring and real-world clinical or спортив contexts.

Recent advances in information technologies, particularly in 3D sensor systems and data-driven modeling, have significantly expanded the possibilities of biomechanical analysis. Inertial Measurement Units (IMUs), depth cameras, and optical tracking systems enable continuous acquisition of motion data with increasing portability and affordability. These technologies allow the capture of high-dimensional motion signals that reflect the underlying biophysical processes

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of human movement. However, raw sensor data are often affected by noise, drift, and sensor misalignment, necessitating advanced signal processing and data fusion techniques.

Machine learning and deep learning methods have emerged as powerful tools for modeling complex, nonlinear, and time-dependent biomechanical signals. Algorithms such as Random Forest, Long Short-Term Memory (LSTM) networks, and Transformer-based models can learn latent patterns from large-scale motion datasets without explicit physical assumptions. When combined with biophysical feature extraction—such as joint angles, angular velocities, and acceleration profiles—these models provide robust frameworks for movement classification, trajectory prediction, and anomaly detection.

The integration of biophysics and information technologies represents a promising paradigm for next-generation biomechanical systems. By combining physically meaningful representations with data-driven learning, it is possible to enhance model interpretability, accuracy, and generalization. This integrated approach is particularly relevant for applications in clinical rehabilitation, sports performance optimization, human–robot interaction, and intelligent healthcare systems.

Therefore, the objective of this study is to develop and evaluate an integrated biophysics–IT framework for modeling human biomechanical movements using 3D sensor technologies and machine learning algorithms. The proposed approach focuses on gait and upper limb motion analysis, incorporating multi-sensor data acquisition, biophysical signal processing, and advanced machine learning models to achieve accurate and reliable movement assessment.

Materials and Methods

Human biomechanical movement data were collected using an integrated multi-sensor system that combined inertial measurement units, optical motion capture technology, and depth-based cameras. This approach allowed complementary

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acquisition of kinematic information related to gait and upper limb movements. IMU sensors, consisting of triaxial accelerometers, gyroscopes, and magnetometers, were attached to key body segments and operated at a sampling frequency of 100–200 Hz. These sensors provided continuous measurements of linear acceleration and angular velocity, which are essential biophysical variables for reconstructing segment orientation and joint kinematics. Optical motion capture systems were employed as a reference standard due to their high spatial accuracy, with reflective markers placed on anatomical landmarks corresponding to major joints. Depth sensors enabled markerless skeletal tracking by reconstructing three-dimensional point clouds and estimating joint positions in real time, offering practical applicability outside laboratory environments.

Raw sensor signals were subject to biophysical signal processing to ensure reliable motion representation. High-frequency noise was attenuated using Butterworth low-pass filters applied to acceleration and angular velocity signals. Sensor drift, particularly prominent in IMU-based measurements, was reduced through sensor fusion techniques based on Kalman filtering, including extended Kalman filter implementations. Orientation estimation was performed using quaternion-based representations to avoid singularities and discontinuities associated with Euler angle formulations. Based on reconstructed orientations, biomechanical parameters such as joint angles, angular velocity, and angular acceleration were computed, reflecting the kinematic behavior of human movement governed by physical laws.

Movement sequences were segmented into meaningful biomechanical phases to facilitate temporal analysis. Gait cycles were divided into stance and swing phases, while upper limb movements were segmented into initiation, execution, and termination phases. This phase-based segmentation enabled structured extraction of time-dependent features and improved the interpretability of subsequent modeling results.

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The extracted biomechanical features were used to train machine learning and deep learning models for movement classification and trajectory prediction. Classical machine learning algorithms, including support vector machines and random forest classifiers, were employed as baseline models due to their robustness and interpretability. For modeling temporal dependencies in biomechanical signals, deep learning architectures such as long short-term memory networks and gated recurrent units were applied. In addition, Transformer-based models incorporating attention mechanisms were implemented to enhance the modeling of long-range temporal relationships and real-time motion prediction. Model training was conducted in a supervised learning framework, with the dataset divided into training, validation, and testing subsets using a 70/20/10 ratio. Model performance was evaluated using classification accuracy and trajectory prediction error metrics.

The overall methodology represents integrated biophysics–information technology framework, in which physically meaningful motion parameters derived from biomechanical principles are combined with data-driven machine learning models. This integration enables accurate, interpretable, and scalable analysis of human biomechanical movements, providing a solid methodological foundation for applications in clinical rehabilitation, sports performance assessment, robotics, and intelligent biomedical systems.

Results

The experimental evaluation demonstrated that the proposed integrated biophysics–information technology framework effectively captured and modeled human biomechanical movements using different 3D sensor modalities. Comparative analysis of sensor technologies revealed that optical motion capture systems achieved the highest spatial accuracy, with overall movement reconstruction accuracy ranging between 97% and 99%. IMU-based systems showed slightly lower accuracy due to sensor drift and cumulative integration

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errors; however, their portability and real-time capabilities made them highly suitable for continuous monitoring, achieving reliable performance levels above 90% after signal filtering and sensor fusion. Depth-based cameras provided a practical markerless alternative, with accuracy values ranging from 85% to 93%, depending on lighting conditions, camera placement, and movement complexity. Machine learning and deep learning models demonstrated strong performance in analyzing and interpreting biomechanical signals. The Long Short-Term Memory model achieved an accuracy of approximately 94% in classifying gait phases, successfully distinguishing between stance and swing phases based on temporal kinematic features. Transformer-based models showed superior performance in predicting upper limb movement trajectories, reaching prediction accuracies of up to 96% and effectively capturing long-range temporal dependencies in motion sequences. Classical machine learning approaches, such as Random Forest classifiers, demonstrated robust performance when applied to IMU-derived features, achieving approximately 90% accuracy in detecting abnormal gait patterns associated with movement impairments.

The integration of biophysical feature extraction with data-driven learning significantly improved model stability and interpretability. Joint angles, angular velocities, and acceleration profiles derived from physically meaningful representations contributed to consistent learning behavior across different sensor modalities. The results indicate that combining multiple sensor types enhanced overall system robustness, reducing the impact of individual sensor limitations and improving generalization across subjects.

Overall, the obtained results confirm that the proposed biophysics–IT integrated approach enables accurate, reliable, and scalable modeling of human biomechanical movements. The findings highlight the potential of this framework for objective movement assessment in clinical rehabilitation, sports performance analysis, early detection of motor disorders, and the development of intelligent human–machine interaction systems.

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Discussion

The findings of this study highlight the effectiveness of integrating biophysical principles with information technology-driven approaches for the analysis of human biomechanical movements. The results demonstrate that physically meaningful kinematic features combined with machine learning models enable accurate representation and interpretation of complex human motion patterns. This integration allows not only high classification and prediction performance but also improved interpretability of model outputs, which is essential in biomedical and clinical applications.

Differences observed among the evaluated 3D sensor technologies reflect inherent trade-offs between accuracy, portability, and environmental constraints. Optical motion capture systems provided the highest level of spatial precision; however, their dependency on controlled laboratory conditions and marker visibility limits their applicability in real-world settings. In contrast, IMU-based systems offered greater flexibility and suitability for long-term and ambulatory monitoring, despite being susceptible to sensor drift and cumulative errors. The application of biophysical signal processing techniques, such as Kalman filtering and quaternion-based orientation reconstruction, significantly reduced these limitations and enhanced the reliability of IMU-derived measurements.

Depth-based camera systems demonstrated moderate accuracy but presented a valuable compromise between ease of use and performance. Their markerless nature and relatively low cost make them attractive for clinical screening, home-based rehabilitation, and large-scale movement analysis. However, sensitivity to lighting conditions, occlusions, and complex movements remains a challenge, emphasizing the importance of sensor fusion strategies that combine complementary data sources.

The machine learning results indicate that deep learning architectures are particularly effective for modeling temporal dependencies in biomechanical signals. Recurrent neural networks, such as LSTM and GRU models, showed

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strong performance in gait phase recognition, while Transformer-based models achieved superior trajectory prediction accuracy due to their attention mechanisms. Nevertheless, these models require large and diverse datasets to achieve robust generalization. Limited training data may lead to overfitting and reduced performance across different subjects and movement conditions, underscoring the need for data augmentation and subject-independent training strategies.

From a biophysical standpoint, incorporating kinematic constraints and physically interpretable features improved the stability and generalization of the learning models. This hybrid approach bridges the gap between purely data-driven methods and traditional biomechanical modeling, providing a more comprehensive understanding of human movement. Such integration is particularly relevant for applications in rehabilitation, where clinicians require both quantitative accuracy and physiological interpretability.

Overall, the discussion emphasizes that the successful analysis of human biomechanical movements depends on the careful integration of sensor technology, biophysical modeling, and machine learning. Future research should focus on expanding multimodal datasets, improving real-time performance, and incorporating additional physiological signals to further enhance system robustness and clinical relevance.

Conclusion

The present study demonstrates that integrating biophysical principles with information technologies provides a robust framework for modeling and analyzing human biomechanical movements. By combining multi-sensor 3D data acquisition, advanced signal processing, and machine learning techniques, the proposed approach achieves high accuracy in gait phase classification, upper limb trajectory prediction, and detection of abnormal movement patterns. The results confirm that the inclusion of physically meaningful features, such as joint angles,

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angular velocities, and accelerations, enhances model interpretability and generalization across different sensor modalities and subjects.

This integrated biophysics–IT methodology has significant implications for clinical rehabilitation, sports performance assessment, robotics, and intelligent human–machine interaction systems. Multi-sensor fusion not only compensates for the limitations of individual technologies but also enables reliable real-time analysis in both laboratory and real-world environments. Deep learning models, particularly LSTM and Transformer architectures, effectively capture temporal dependencies in biomechanical signals, highlighting their potential for predictive and adaptive applications.

Future developments may focus on incorporating additional physiological signals, implementing haptic feedback and robotic support systems, and expanding datasets to include diverse populations and movement types. Such enhancements would further improve system robustness, clinical relevance, and applicability in intelligent healthcare and assistive technologies. Overall, the study establishes a comprehensive, scalable, and interpretable framework for human biomechanical movement analysis, bridging the gap between traditional biophysical modeling and modern information technology-driven approaches.

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