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Reviewing Current Trends: Machine Learning for risk assessments of Occupational Exoskeletons

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INTRODUCTION

There are rising musculoskeletal injuries due to poor posture and physical exertion in workplaces. Occupational exoskeletons as assistive wearable solutions are implemented to reduce injury risk. This poster aims to review existing machine learning (ML) systems with sensor technologies that assess risk for occupational exoskeletons.

Examples of various exoskeletons: (1) Passive arm exoskeleton WREX, (2) HAL from Cyberdyne, Japan, (3) ARMin III rehabilitation arm, (4) ActiveLinks Powerloader Ninja exoskeleton suit, (5) NaTUre-gaits, and (6) E-leg exoskeleton from Ekso Bionics.

BACKGROUND

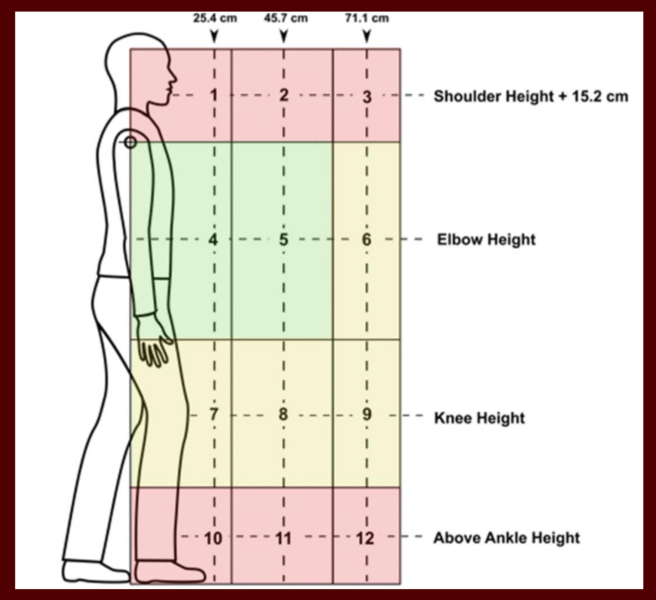
- Exoskeleton Technology: Wearable devices designed to assist workers by enhancing physical capabilities.
- Wearable sensors on the exoskeleton monitor muscle activity and movement patterns, providing real-time feedback.
- Data from sensors is crucial for developing machine learning models that predict user responses and risks.
- Challenges: Current systems often rely on limited datasets; expanding the variety of sensor data can enhance accuracy of risk prediction and safety for worker.

METHODS

- Analysis of five key studies incorporating ML with sensor data to predict risk.
- Focus on how these studies enhance safety and effectiveness of there prediction in exoskeleton applications.

RESULTS

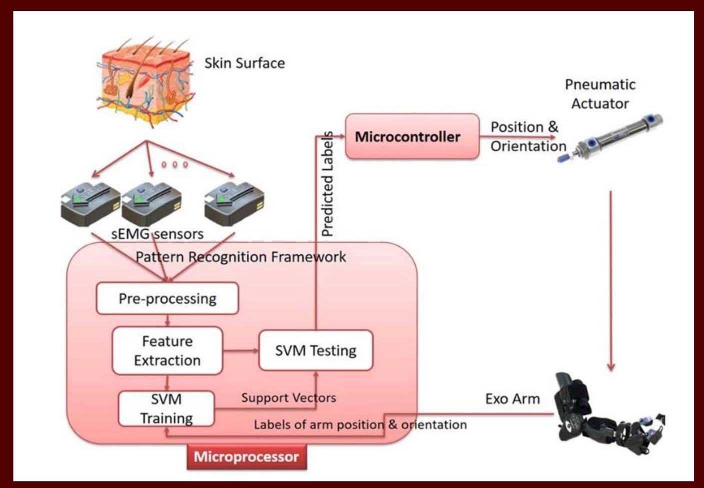
Study 1: Machine Learning for Detection and Risk Assessment of Lifting Action
Objective: Predict muscle fatigue using IMU data and the NIOSH dataset.
Findings: Successfully outputs risk assessments for lifting tasks.
Limitation: Data is limited to two sources, lacking comprehensive measures.
Improvement: Incorporate EMG data and additional metrics for enhanced efficiency.



Lifting zones defined by ACGIH Lifting TLV. Green zones (4-5) indicate Low Risk, yellow zones (6-9) signify Medium Risk, and red zones (1-3, 10-12) represent High Risk. This classification aids in assessing lifting tasks associated with exoskeleton use

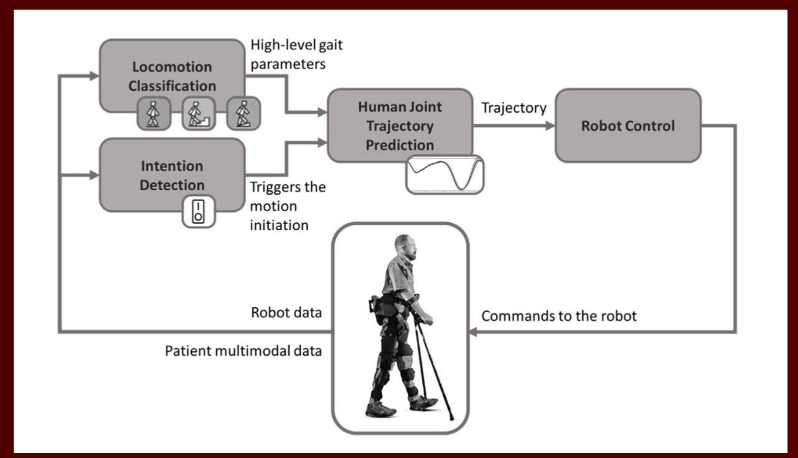
Study 2: Risk Classification of Ergonomic Musculoskeletal Disorders in Work-related Repetitive Manual Handling Operations with Deep Learning Approaches
Objective: Merge multiple datasets for accurate risk assessment in manual handling.
Findings: Utilizes deep learning to identify patterns in lifting tasks.
Limitation: Relies on data augmentation, which reduces accuracy
Improvement: Implement transfer learning method with unique datasets to enhance training.

Study 3: A Machine Learning System for Classification of EMG Signals to Assist Exoskeleton Performance
Objective: Develop algorithms to predict muscle activity for exoskeleton control.
Findings: Achieves high classification accuracy using a multiclass support vector machine.
Limitation: Limited database restricts adaptability to new subjects.
Improvement: Focus on adaptive ML systems that learn from individual EMG patterns.



Flowchart illustrating the machine learning enhanced exoskeleton system. This diagram outlines the process of converting EMG signals into actionable commands for exoskeleton control, highlighting key components such as feature extraction and classification accuracy.

Study 4: AI-based Methodologies for Exoskeleton-Assisted Rehabilitation of Lower-Limb
Objective: Review 31 existing AI methodologies used in lower-limb rehabilitation exoskeletons.
Findings: Identifies most effective techniques to use in predictive model like Reinforcement Learning and Neural Networks.
Limitation: Lacks empirical data on effectiveness in real-world applications.
Improvement: Validate AI methods through practical implementations and experimentations in exoskeleton systems.



Overview of various AI techniques, including Reinforcement Learning and Support Vector Machines, utilized to enhance adaptive control in lower-limb rehabilitation exoskeletons

Study 5: Machine Learning Techniques for Motion Analysis of Fatigue from Manual Material Handling Operations Using 3D Motion Capture Data
Objective: Analyze fatigue during manual material handling using 3D motion capture data and biometric information.
Findings: Developed machine learning models using supervised and unsupervised learning techniques to predict fatigue.
Limitation: Optical motion capture systems are impractical for real-world applications due to space and complexity constraints.
Improvement: Future work should explore inertial motion capture systems and utilize LSTM or GRU networks for better time-series data handling.

DISCUSSION

- Data Integration: Sensors collect real-time data on user movements, muscle activity, and external forces. This data is crucial for training machine learning models that predict user responses and assess risks associated with exoskeleton use.
- Inertial Measurement Units (IMUs): Monitor acceleration and angular velocity to assess movement dynamics.
- Electromyography (EMG) Sensors: Measure electrical activity in muscles, providing insights into muscle activation and fatigue.
- Force Sensors: Gauge load and forces during lifting tasks, contributing to real-time risk assessments.
- ML Applications: Integration of sensor data enhances the predictive capabilities of ML models for risk assessment.
- Adaptive algorithms can learn from individual user interactions, improving personalization and effectiveness in real time.
- Future research should focus on developing adaptive ML systems that can learn from diverse user patterns over time.
- Integration of ML with sensor technology enhances safety and effectiveness of occupational exoskeletons.

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