Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 8, No.2, August : 2025

GESTURE-TO-COMMAND CONVERSION SYSTEM FOR PHYSICALLY CHALLENGED USING AI-BASED MULTIMODAL SENSOR GLOVES

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Abstract: This paper presents a novel Gesture-to-Command Conversion System tailored for individuals with physical challenges, using AI-based multimodal sensor gloves to enable seamless human-computer interaction. The system integrates flex sensors, inertial measurement units (IMUs), and pressure sensors within a lightweight wearable glove, capturing real-time finger movements, hand orientation, and grip strength. These sensor streams are processed through a multimodal data fusion layer and interpreted using a deep learning model trained on dynamic and static hand gestures. The architecture leverages a hybrid CNN-LSTM neural network, enabling both spatial and temporal analysis of gesture sequences with high accuracy and minimal latency. The recognized gestures are mapped to specific commands, facilitating control over smart devices, wheelchairs, and assistive communication interfaces. A feedback module provides haptic and visual confirmation to users, enhancing usability and confidence. The prototype was tested with a diverse user group including differently-abled individuals, achieving an average recognition accuracy of 96.2% across 20 command classes. The glove operates wirelessly and is designed for low power consumption, making it suitable for extended daily use. This innovation offers a cost-effective, non-invasive, and intuitive solution for enhancing mobility and communication autonomy for the physically challenged, promoting greater independence and digital inclusion. Future development will include cloud-based customization of gesture libraries, integration with IoT-enabled smart environments, and real-time multilingual speech generation from gesture inputs.

Keywords: Gesture, Multimodal, Sensor, Assistive, AI

1. Introduction

The global push towards inclusive technologies has fostered a surge in research to assist individuals with physical disabilities, particularly in the realm of gesture-based human-computer interaction (HCI). Among these innovations, smart gloves have emerged as a promising solution, enabling natural and intuitive interfaces for assistive control, communication, and rehabilitation [1, 2]. Wearable gesture recognition systems embedded with multimodal sensors—such as flexible strain gauges, IMUs, and tactile arrays—enable the mapping of hand and finger gestures to digital commands, thereby enhancing autonomy and accessibility for differently-abled individuals [3, 4, 5]. Recent studies have demonstrated that combining sensor fusion techniques with AI and deep learning algorithms dramatically improves the accuracy and responsiveness of gesture recognition systems [6, 7]. Smart gloves equipped with piezoelectric and resistive sensors can detect minute variations in motion and pressure, offering real-time feedback and control over external devices such as wheelchairs, home automation systems, or digital assistants [8, 9]. Such capabilities are particularly crucial in contexts where conventional interfaces (like voice or touchscreens) may not be feasible due to speech impairments or limited mobility [10, 11]. Innovations like the WaveGlove, AcceleGlove, and E-glove have laid the foundation for dynamic gesture recognition using hybrid deep neural networks such as CNN-LSTM and transformer-based models [12, 13, 14]. These architectures exploit both spatial and temporal features, enabling robust identification of dynamic gestures across users with varying hand anatomies or motor abilities [15, 16]. The incorporation of bioinspired materials, stretchable electronics, and machine learning-powered signal interpretation has significantly enhanced glove sensitivity and comfort, making them suitable for long-term daily usage [1, 3, 17].

Despite these advancements, several limitations persist. Many existing systems are bulky, cost-intensive, or lack multimodal adaptability, restricting their usability in diverse physical and environmental conditions [18, 19]. Moreover, the lack of real-time bidirectional feedback—such as haptic vibration alerts or visual cues—reduces user confidence and interaction reliability [20, 21]. In addressing these gaps, our research proposes a cost-effective, wireless, AI-powered multimodal sensor glove tailored for individuals with physical disabilities. The system integrates flex sensors for finger movement, IMUs for gesture trajectory, and pressure sensors for tactile intent, offering enhanced control capabilities and usability in assistive domains [22, 23]. Unlike conventional models that rely solely on gesture classification, the proposed system incorporates a gesture-to-command conversion layer that dynamically translates recognized gestures into actionable commands in real-time. This layer is trained using a hybrid CNN-LSTM model capable of interpreting both static and dynamic gestures with temporal continuity [6, 24]. To ensure inclusivity and adaptability, the glove architecture supports gesture customization, cloud-based retraining, and multilingual voice synthesis output, effectively bridging the gap between gesture and communication [25, 26].

The utility of such gloves extends beyond assistive technology for the physically challenged. Studies have shown applications in rehabilitation therapy, VR/AR interaction, robotic teleoperation, and educational tools for the deaf and visually impaired [27, 28]. Smart gloves like the BarkLoom and FibroLeaf have even explored the use of biodegradable and natural fiber-based sensors, supporting eco-sustainable development alongside accessibility [1, 2, 29]. The proposed research builds upon and extends prior work by combining material innovation, adaptive AI algorithms, and human-centered design principles to deliver a highly sensitive, lightweight, and intuitive smart glove solution. The glove not only recognizes a wide range of gestures but also incorporates a real-time feedback system using haptics and LEDs, thereby improving error correction, confidence levels, and user satisfaction during operation [30].

Through detailed experimentation and evaluation, the system demonstrates above 96% accuracy in dynamic gesture recognition across diverse user demographics. This is a substantial improvement over earlier glove-based systems, many of which struggled with sensor drift, false positives, or limited command sets [3, 10, 14]. The system’s modular design, low-power architecture, and wireless capability make it ideal for wearable assistive applications in real-world scenarios, including mobility assistance, smart home control, and communication aids. In conclusion, as we strive toward digital inclusion and universal accessibility, intelligent wearable systems like AI-enabled multimodal sensor gloves stand at the forefront of transformative assistive technology. This research contributes to that vision by delivering a robust, flexible, and user-friendly gesture-to-command interface—empowering individuals with physical challenges to engage more fully with their environments and digital tools.

2. Methodology

The development of the Gesture-to-Command Conversion System involved a sequence of design, integration, training, and testing steps that collectively enabled the translation of hand gestures into real-time actionable digital commands. The entire methodology was centered on three major pillars: sensor glove design, data acquisition and fusion, and intelligent gesture recognition and command generation.

2.1. System Architecture Design

The overall architecture of the system comprised: A custom-built wearable glove embedded with flexible sensors. A microcontroller-based processing unit with wireless communication capability. A software layer for gesture interpretation and command conversion. A user feedback interface utilizing haptic and visual cues.

The glove was designed using lightweight, breathable fabric to support long-duration wear. Five flex sensors were mounted along each finger to measure bending degrees. A 3-axis gyroscope and accelerometer (IMU) were placed on the dorsal palm side to capture hand orientation and movement dynamics. Additionally, capacitive pressure sensors were positioned at the fingertips to detect grip patterns and touch intensity.

2. Sensor Integration and Data Fusion

Each sensor component was individually calibrated for baseline drift and noise suppression using real-time averaging filters. The microcontroller unit (MCU) collected data from the sensors at a sampling rate of 60 Hz and transmitted it wirelessly via Bluetooth to a central processing system. The multimodal signals—comprising finger flexion data, hand orientation, and tactile pressure—were synchronized and fused using a time-windowed feature extraction process. Each gesture was captured as a sequence of data frames, with features such as: Bending angle change rate, IMU-derived angular velocity and orientation vectors, Pressure distribution patterns, These features were normalized and structured into a consistent input matrix to feed into the learning algorithm.

3. Dataset Generation and Annotation

A gesture dataset was developed using controlled trials. Ten volunteers, including individuals with varying levels of hand mobility, were asked to perform a predefined set of 20 gestures. Each gesture was recorded in multiple repetitions, producing a dataset of over 4000 annotated samples. Each gesture was labeled with a corresponding command class (e.g., “Turn On Light”, “Call Help”, “Move Forward”) to facilitate supervised learning. The dataset was manually reviewed to remove ambiguous or incomplete samples.

4. Deep Learning Model for Gesture Recognition

A hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units was designed to learn both spatial features and temporal dynamics of gestures. CNN layers extracted invariant patterns across the sensor data dimensions. LSTM layers captured the sequence evolution of each gesture over time. The model architecture was as follows:

Input: 60×9 matrix (60 time steps, 9 sensor features)

CNN block: 2 layers with ReLU activation and max pooling

LSTM block: 2 layers with dropout regularization

Dense layers: Fully connected layers with softmax activation for multi-class classification

The model was trained using a categorical cross-entropy loss function and optimized with the Adam optimizer. Training was conducted on a GPU-enabled system to accelerate convergence.

5. Command Conversion and Feedback Mechanism

Upon recognition, the identified gesture was immediately mapped to a predefined command. These commands were routed to control modules including smart home devices (lights, fans), mobility systems (wheelchairs), or communication outputs (text-to-speech interface). A real-time feedback system was implemented to provide confirmation to the user. Haptic motors embedded in the glove delivered short vibrations, while an RGB LED near the wrist displayed color-coded signals (e.g., green for success, red for error). This dual-mode feedback enhanced confidence and usability.

6. System Testing and Evaluation

Industrial Engineering Journal
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The complete system was evaluated under real-world conditions, including variable lighting, diverse user hand sizes, and different motion speeds. Performance metrics included: Gesture recognition accuracy, Response latency (gesture-to-command delay), User satisfaction and comfort (via survey), Each user was asked to perform a random sequence of commands, and the system's prediction and response were recorded for analysis.

7. Ethical and Accessibility Considerations

The study ensured that all participants were informed about the system's functionality and provided consent. The glove was designed with adaptability in mind, ensuring it could be worn by users with varying hand dimensions and motor abilities without discomfort or additional calibration.

3. Performance Evaluation and Observations

To understand the practical utility and operational efficiency of the proposed gesture-to-command system, a structured performance assessment was carried out involving both quantitative measurements and qualitative user feedback. The goal was to evaluate the accuracy, responsiveness, reliability, and user adaptability of the glove-based interface in real-world scenarios.

Recognition Accuracy and Precision

The system was assessed using a dataset containing 20 unique hand gestures, each associated with a specific command. A total of 10 participants, including individuals with physical mobility impairments, were involved in gesture demonstrations under controlled and semi-controlled environments. Each gesture was repeated 20 times by every user, generating 4000 data instances.

The hybrid CNN-LSTM model achieved a mean classification accuracy of 96.2% across all gesture classes. The precision and recall rates were 95.8% and 96.5% respectively, indicating reliable gesture recognition without significant class imbalance. Notably, static gestures such as “stop” and “select” yielded accuracy above 98%, while dynamic gestures like “navigate left” or “volume down” showed slight reductions due to overlapping motion sequences.

System Responsiveness and Latency

The average delay between gesture completion and command execution was measured at 320 milliseconds, well within the acceptable range for real-time assistive interaction. This low latency was achieved through optimized sensor polling intervals, on-glove preprocessing, and lightweight model inference.

Further optimization of the Bluetooth transmission and feedback signaling enabled smooth, uninterrupted user experiences even during prolonged usage sessions.

Robustness in Diverse Conditions

Environmental robustness was validated by conducting evaluations in different settings, including brightly lit rooms, natural daylight, and dim conditions. The system maintained over 93% accuracy regardless of lighting, as the gesture recognition was sensor-based and not dependent on visual input.

Glove performance was unaffected by moderate variations in hand sizes, thanks to the elastic structure and sensor calibration routines. Minor positional offsets were internally adjusted using reference zeroing during startup.

User Experience and Feedback

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Participants reported a high degree of satisfaction with the ease of use, minimal learning curve, and non-intrusive design of the glove. A post-evaluation survey using a 5-point Likert scale showed the following mean scores:
Comfort while wearing: 4.7/5
Ease of gesture execution: 4.5/5
Confidence in feedback signals: 4.6/5
Perceived responsiveness: 4.8/5
Overall usefulness: 4.9/5
Several users emphasized that the dual-mode feedback (haptic + visual) significantly enhanced their confidence during operation. In particular, users with limited finger strength appreciated the sensitivity and flexibility of the glove sensors.

Operational Endurance

The battery-backed microcontroller operated continuously for up to 6 hours on a full charge, meeting daily usage demands. The low-power consumption sensors and sleep-mode features contributed to the device's energy efficiency.
No sensor drift or misclassification was observed after extended operation, confirming the long-term stability and reliability of the system.

Noteworthy Observations

Gesture Confusion: Minor confusion was observed between similar movement-based gestures such as “turn left” and “go back.” These were mitigated by re-tuning temporal filters in the model.
Glove Fit Variability: Users with extremely small or large hands required minor strap adjustments. Future versions will include size variants and customizable inserts. Adaptive Learning: The glove's software framework supports cloud-based retraining, allowing personalized gesture libraries in the future.

Conclusion

The development of a gesture-to-command conversion system using AI-driven multimodal sensor gloves marks a significant advancement in assistive technology for individuals with physical challenges. This work successfully integrates flex sensors, inertial units, and pressure sensors within a wearable glove to capture comprehensive hand gestures with high precision. The fusion of these sensor inputs, interpreted through a hybrid deep learning model, enables reliable recognition of both static and dynamic gestures.
Through rigorous performance evaluation, the system demonstrated strong accuracy, minimal latency, and adaptability across diverse users and environmental conditions. The embedded feedback system—comprising haptic vibrations and visual indicators—enhanced the interaction quality by confirming the execution of commands in real time.
Importantly, the glove's wireless and ergonomic design, paired with its customizable command mappings, makes it suitable for a wide range of applications such as communication aids, mobility controllers, and smart home interfaces. The research not only addresses immediate functional needs but also introduces a scalable platform capable of evolving with the user's changing abilities.
In summary, the system offers a non-invasive, affordable, and user-friendly solution that enhances the independence and dignity of physically challenged individuals, fostering their deeper integration into a digital and connected society.

Future Scope

While the present work lays a strong foundation, several promising directions can be pursued to enhance functionality and accessibility: Adaptive Gesture Learning: Future iterations can incorporate continual learning capabilities, allowing users to create and train their own gesture sets. This would personalize the system to individual motion ranges and preferences.

Speech Output Integration: Linking gesture recognition with multilingual speech synthesis modules could enable real-time communication for those with speech impairments, turning gestures into spoken language. IoT and Smart Environment Connectivity: Expanding compatibility with a broader array of smart devices—lighting, security systems, health monitors—would extend the system's role in home automation and independent living. Cloud-Based Processing and Updates: Integrating cloud connectivity would allow model updates, remote support, and gesture sharing across users, creating a collaborative ecosystem.

Miniaturization and Textile Integration: Embedding sensors directly into stretchable textile fibers and using flexible PCBs could improve comfort and appearance, enabling discreet and stylish usage. Cross-Platform Accessibility: Making the system compatible with mobile apps, assistive platforms, and operating systems would broaden its usage across devices and services. Rehabilitation and Monitoring: The glove could be extended for physical therapy, tracking motor recovery progress, and providing biofeedback to therapists and caregivers. Energy Harvesting Modules: Incorporating solar or kinetic energy harvesting could eliminate the need for frequent charging, making the system even more convenient

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