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Design and Implementation of a Sensor-Based Wearable Glove for Real-Time Sign Language Recognition

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Abstract

This paper presents a real-time sign language conversion using a wearable glove system utilizing multi-sensor data acquisition and machine learning-based gesture classification. The system employs flex sensors to capture finger articulation along with an inertial measurement unit to track hand orientation and real-time movement." The acquired analog signals are processed and then classified into feature vectors, which are then used for classification of predefined gesture patterns using a trained learning model."

Introduction

Communication through sign language plays a crucial role for individuals with hearing and speech impairments; however, the lack of widespread understanding of sign language creates a significant communication gap in daily interactions. Existing translation approaches are predominantly based on vision-driven techniques, which rely on camera input and complex image processing algorithms. Although such systems demonstrate high accuracy under controlled conditions, their performance is often affected by environmental factors such as lighting variations, background complexity, and camera positioning, reducing on-the-go and live-use situations.

To address these limitations, this work focuses on the creation of a sensor-equipped hand-worn device that converts finger movements into readable text instantly. Unlike conventional approaches, the designed setup directly records finger bending and hand motion using flex sensors and an inertial sensing unit, thereby eliminating dependency on external vision modules. This enables reliable data collection regardless of environmental changes, with minimal processing power needed.

The main goal of this project is to a compact, efficient, and user-friendly assistive system that can facilitate seamless bridging the gap between gesture-based communicators and those unfamiliar with such methods. By combining sensor-based data acquisition with intelligent classification, the proposed approach aims to provide a practical alternative to existing methods while ensuring real-time responsiveness and scalability for future enhancements.

During implementation, multiple gesture samples were recorded and analysed to ensure stable classification across variations in hand movement and user-specific differences.

Related Work

Researchers have widely explored sign language detection to enhance communication for people with hearing and speech difficulties. A large number of most current systems rely on camera-based methods where hand movements are recorded and analysed using visual data analysis and advanced neural network architectures like CNNs. such methods have demonstrated promising accuracy; however, their performance is highly dependent on environmental factors such as lighting conditions, background complexity, and camera alignment (Zhang et al., 2020). Additionally, continuous image processing leads to increased computational complexity, making real-time implementation challenging on resource-constrained systems.

To overcome these limitations, sensor-based approaches have been introduced, particularly using hand-worn devices fitted with bend-detecting sensors to track finger movement such setups offer a more stable and environment-independent solution for gesture acquisition. However, early sensor-based implementations relied on rule-based or threshold-based techniques, which restricted their scalability and reduced detection performance while handling a larger set of gestures (Kumar and Singh, 2019).

Recent research has focused on integrating inertial sensors such as accelerometers and gyroscopes along with flex sensors to capture both static and dynamic aspects of hand gestures. This multi-sensor approach improves the overall representation of gestures and enhances recognition capability. Even with these improvements, issues like sensor noise, variations in user hand motion, and efficient feature extraction still affect system performance (Patil et al., 2021).

The progress of gesture communication technology can be analysed based on different technological approaches and their limitations:

- Deep Learning-Based Vision Systems:

Advanced systems employed deep learning models to the independently identify positional patterns from hand movement visuals

although these methods improved recognition accuracy, they introduced high computational complexity required continuous video input reducing their suitability for battery-saving and instant response uses.

- Single-Sensor Wearable Systems:

Wearable gloves using only flex sensors were developed to capture finger bending patterns. While these systems reduced environmental dependency, they lacked the ability to capture dynamic motion, leading to ambiguity in gestures with similar finger configurations.

- Inertial Sensor Integration:

To address motion-related limitations, inertial measurement units were incorporated to capture acceleration and orientation data. This enabled detection of dynamic gestures; however, challenges such as signal drift, noise, and calibration errors affected system reliability.

- Features Engineering Techniques:

Multiple data processing techniques, such as mathematical measures and time-based analysis, were applied to turn unprocessed sensor readings into useful information. Inefficient feature selection often leads to redundancy and affects classification performance.

- Machine Learning-Based Classification:

Sorting methods like SVM and deep learning networks were used to enhance detection performance. Despite better generalization, these models are sensitive to training data quality and may introduce latency when handling larger gesture sets.

- System-Level Challenges:

Existing systems face trade-offs between accuracy, computational efficiency, and real-time responsiveness. Many implementations either lack portability or fail to deliver steady results among varying users and environmental conditions.

Based on these observations, there exists a strong need for a system that ensures efficient feature representation, low-latency processing, and robust gesture classification. The proposed work addresses these aspects by integrating multi-sensor data acquisition with an optimized processing pipeline for real-time sign language translation.

In contrast, wearable sensing technologies introduced a more deterministic approach to gesture acquisition by directly measuring physical parameters such as finger flexion and hand orientation. Flex sensor-based gloves provided a simplified data representation; however, the lack of movement-based tracking restricted their capacity to tell apart signs that look nearly identical when stationary. This limitation led to the incorporation of inertial sensing units, enabling the capture of temporal motion patterns along with spatial finger positioning.

The integration of heterogeneous sensor data necessitated the use of effective data handling methods for feature extraction and dimensionality reduction. Several studies have explored statistical and time-domain features to represent gesture patterns, followed by categorization through AI-based methods like SVM and neural network models. While these methods improved detection results, their output is frequently affected by inter-user variability and sensor noise, requiring robust preprocessing mechanisms.

Moreover, achieving low-latency processing remains a critical challenge in wearable gesture recognition systems. Many existing solutions either prioritize accuracy at the cost of computational complexity or compromise performance for faster execution. This trade-off points to the necessity of a combined strategy that guarantees real-time responsiveness and reliable gesture interpretation.

Considering these challenges, the present work emphasizes a structured pipeline that integrates multi-sensor.

From the critical analysis of existing approaches, it is clear that no individual technique fulfils all needs of compactness, processing speed and steady live performance together. Vision-based systems, although accurate, impose high processing overhead and are constrained by environmental dependencies. In contrast, glove-based systems offer a steadier data collection approach but often suffer from limited feature representation and challenges in handling dynamic gesture variations.

Moreover, the integration of multiple sensors introduces additional complexity in terms of data synchronization and noise management, which directly impacts classification reliabilityalthough AI-based methods have enhanced detection ability,the balance between model complexity and response time remains a key concern in real-time applications.

Methodology

The developed setup is built as a wearable glove-based interface for real-time sign language translation, integrating multi-sensor data acquisition with an efficient gesture recognition pipeline. The overall methodology focuses on capturing hand gestures, processing sensor data, and generating corresponding textual output with minimal latency.

1) System Architecture:

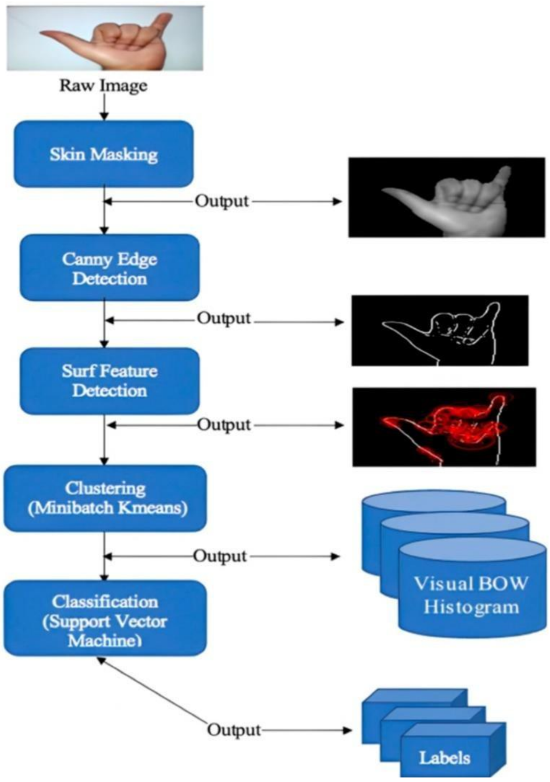
The system follows a structured flow consisting of sensor data acquisition, signal processing, feature extraction, and classification. Flex sensors and motion tracking module is applied as primary input sources. Analysed readings are matched to fixed hand signs to produce results instantly.

2) Sensor Data Acquisition:

Bendable detectors track how much each finger curves by producing variable resistance, later changed into electrical readings. An inertial sensor captures wrist direction and movement behavior. These Analog signals are continuously sampled and digitized using a microcontroller, ensuring real-time data capture.

3) Feature Extraction:

Key characteristics are pulled from the filtered sensor data to represent gesture patterns effectively. These features include finger bend levels and motion-related parameters obtained from inertial data. The extracted values are merged to build a feature vector representing each gesture instance.



4) Gesture Classification:

The feature vectors act as feed for a classification mechanism that identifies the corresponding gesture. A supervised learning approach is utilized, where predefined gesture patterns are mapped to specific output labels. This enables the system to differentiate among multiple gestures with improved accuracy.

5) Sensor Calibration and Data Stability:

To ensure reliable gesture recognition, an initial calibration process is performed for all sensors before system operation. Calibration helps in setting baseline readings for various finger positions and minimizes variations caused by sensor drift or individual hand differences. During this process, baseline readings are recorded and used to normalize incoming sensor data. This improves consistency in feature extraction and enhances overall classification accuracy. Additionally, minor fluctuations in sensor output are handled through stabilization techniques to maintain uniform data representation across different gesture inputs.

System Workflow

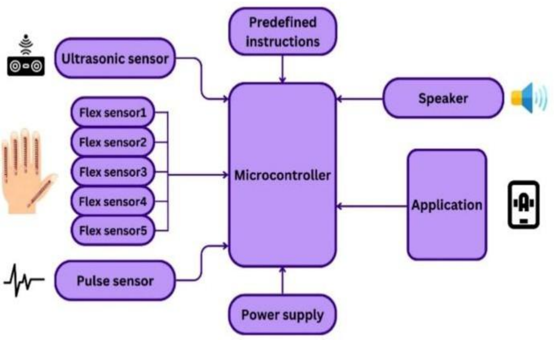
The complete working of this setup is outlined below:

1. Capture real-time sensor data from the glove.
2. Change continuous signals into discrete.
3. Apply preprocessing techniques to stabilize the data.
4. Pull out significant patterns from detector readings.
5. Classify the gesture using a trained model or mapping logic.
6. Generate the corresponding textual output.

Output Generation

Once a gesture is identified related text is shown, enabling communication in a live processing system. The system is designed to ensure quick response with minimal processing delay, making it suitable for assistive applications.

The methodology emphasizes a proper equilibrium between processing speed and identification precision, keeping the platform responsive while maintaining reliable performance across different gesture inputs.



The overall system architecture and processing flow of the developed hand gesture interpretation framework are illustrated in the following figures. The diagrams represent the step-by-step execution of gesture acquisition, processing, and output generation:

1) Gesture Classification:

Derived data patterns are passed into a trained classifier, such as Support Vector Machine(SVM)or a simple Neural Network, to classify predefined gesture patterns.

2) Darta Pre-processing:

The acquired sensor data is normalized and cleaned to eliminate irregularities fluctuations. This step ensures stable and consistent input for pattern identification.

3) Real-Time Processing:

The entire pipeline is optimized to ensure low-latency performance, enabling immediate response to user gestures.

4) Communication Interface:

The processed data is transmitted wirelessly to an external device such as a smartphone via Bluetooth for visualization and interaction.

5) Clustering Mechanism:

The derived characteristics are arranged through Mini Batch K-Means clustering to form a structured representation known as a visual feature set.

6) Signal Coversion:

Continuous electrical outputs from detectors are changed into numerical values using the analog-to-digital converter(ADC) of the microcontroller for further processing.

7) Classification:

An SVM algorithm is applied to sort each sign using generated feature vectors and assign corresponding labels.

8) Output Generation:

The classified gesture is mapped to predefined outputs, completing the recognition process.

9) Sensor Integration:

The system incorporates multiple flex sensors positioned on fingers to capture bending patterns, combined with extra detectors for movement and activity tracking.

10) Signal Acquisition:

Each sensor generates analog signals corresponding to physical movements, which are continuously monitored by the microcontroller.

11) Microcontroller Processing:

The microcontroller acts as the central processing unit, where sensor data is collected, digitized, and processed for gesture interpretation.

12) Predefined Gesture Mapping:

Device readings are matched against with predefined instruction sets or trained patterns to identify specific gestures.

13) Data Communication:

Processed data is transmitted to external modules such as a mobile application or output interface for further interaction.

14) Output Interface:

Detected hand signs are changed into meaningful outputs such as text or audio signals through connected devices like speakers.

15) Power Management:

A stable power supply ensures continuous system operation and consistent sensor performance.

Implementation

The implementation phase focuses on the practical realization of the proposed system by integrating sensing, processing, and communication modules into a unified wearable platform. Emphasis is placed on accurate gesture acquisition and reliable signal interpretation under real-time conditions. The system is built to maintain consistency in performance while ensuring user comfort and flexibility. The following figure illustrates the developed prototype and its functional components.

- Prototype Realization:

The proposed system was physically implemented in the as a wearable glove integrated with multiple flex sensors positioned along each finger. The sensors were carefully aligned to capture bending variations corresponding to different hand gestures.

- Sensor Integration and Signal Capture:

Each flex sensor generates variable resistance based on finger movement. These variations are changed into voltage signals and continuously monitored by the processing unit. The placement of sensors ensures that even minor finger movements are effectively captured.

- Gesture Interpretation Mechanism:

The captured sensor values are mapped to specific gesture patterns. Different combinations of finger positions result in unique signal patterns, which are identified and translated into meaningful outputs.

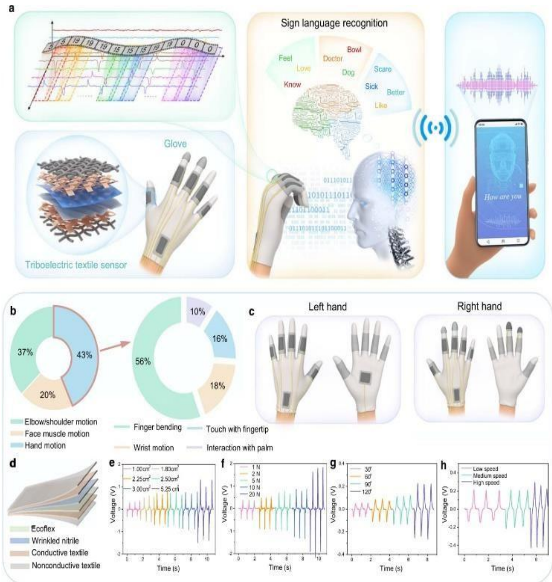
- Wireless Communication Interface:

The processed data is transmitted to an external device, such as a smartphone application, where the recognized gesture is displayed. The system supports real-time interaction, ensuring minimal delay between gesture input and output.

- Output Representation:

Recognized gestures are changed into both visual and audio outputs. As shown in the figure, the interpreted gesture is shown as text on the mobile interface and can also be converted into speech for better accessibility.

The implemented system demonstrates effective integration of sensing and processing components for reliable gesture acquisition.



Results

The system performance was tested using accuracy analysis for each gesture. The obtained results show that most of the set gestures were identified correctly, showing the effectiveness of the implemented mapping strategy. Variations in accuracy were observed for gestures involving similar finger configurations, which led to minor minor errors. The graphical representation highlights the system stability across multiple trials, while the real-time output images validate the practical functionality of the developed prototype.

The obtained results clearly demonstrate the reliability, efficiency, and real-time capability of the proposed system, making it a viable solution for assistive communication applications.

Conclusion

The proposed system presents an efficient and practical approach for real-time sign language recognition using a sensor-based wearable glove. The integration of flex sensors with a compact processing unit enables accurate capture and interpretation of hand gestures. The implemented system demonstrates reliable performance with minimal latency, ensuring smooth and responsive communication.

The experimental results indicate that the system maintains consistent accuracy across

multiple gestures, while effectively handling minor variations in sensor inputs. The simplicity of the gesture mapping approach contributes to reduced computational complexity, making the system suitable for real-time applications.
Overall, the developed prototype validates the feasibility of using a wearable interface for assistive communication, offering a low-cost and user-friendly solution for bridging the gap between sign language users and non-sign language users.
The presented work highlights the potential of sensor-driven wearable systems in enabling efficient human–machine interaction. The proposed system establishes a robust foundation for future advancements in intelligent wearable interfaces, paving the way for more adaptive and context-aware sign language translation systems.
The experimental observations confirm that the implemented approach effectively handles variations in sensor data while maintaining stable recognition accuracy. The low-latency response achieved by the system supports real-time interaction, which is essential for practical assistive applications. Additionally, the simplified mapping mechanism contributes to reduced computational complexity without compromising system performance.
Furthermore, the proposed framework offers flexibility for future enhancements, including the integration of advanced learning algorithms and expanded gesture sets. The overall design ensures scalability and adaptability for evolving communication needs. The presented system demonstrates a reliable integration of sensor-driven data acquisition and real-time processing, achieving stable performance with minimal latency. It establishes a scalable and efficient framework for developing advanced wearable solutions in gesture-based human–machine interaction and assistive communication.

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