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Virtual Mouse Using Wireless Glove with Machine Learning

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Abstract

The evolution of human-computer interaction (HCI) has opened avenues for intuitive and immersive interfaces. This paper presents the design and development of a virtual mouse system controlled by a wireless glove integrated with inertial measurement sensors and flex sensors. By applying machine learning algorithms, the system accurately maps hand gestures to mouse functionalities such as cursor movement, clicks, and drag operations. The glove communicates wirelessly with a computer via Bluetooth, enabling real-time interaction. Our proposed solution provides a cost-effective and accessible alternative to conventional input devices, especially beneficial in fields such as virtual reality, robotics, and accessibility technologies.

Keywords: Virtual Mouse, Wireless Glove, Human-Computer Interaction, Machine Learning, Gesture Recognition, Bluetooth Communication.

I. Introduction

Traditional computer input devices such as mice and keyboards pose limitations in modern immersive environments. As gesture-based interfaces gain traction, virtual mouse systems that respond to natural hand movements offer significant promise in enhancing user experience [1]. Wearable technology, particularly wireless gloves equipped with sensors, enables seamless gesture capture without restricting user mobility. Integrating machine learning further improves the accuracy and adaptability of such systems to diverse user behaviors.

This paper introduces a virtual mouse system implemented using a wireless glove. The glove uses flex and inertial sensors to track finger and hand movements processed using a supervised learning model to interpret gestures. Wireless data transmission via Bluetooth ensures untethered interaction with the host system.

II. Related Work

Several studies have explored gesture-based input methods. Sharma et al. [2] proposed a glove-based control system using accelerometers, while Kim et al. [3] demonstrated the application of EMG sensors for gesture recognition. More recent advancements have integrated machine learning models to enhance gesture classification accuracy [4]. However, many systems are either wired or lack real-time responsiveness.

In contrast, our approach emphasizes real-time performance, wireless operation, and a flexible machine learning backend to ensure robust gesture [8] interpretation across users.

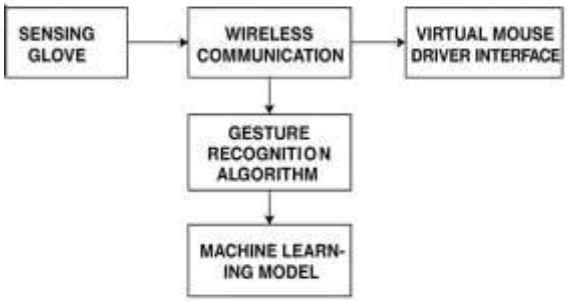
III. System Architecture

The proposed system comprises four major components: the sensing glove, wireless communication module, gesture recognition algorithm, and virtual mouse driver interface.

A. Hardware Design

The glove includes:

- Flex Sensors: Measure finger bending by resistance change[9].
- Inertial Measurement Unit (IMU): Combines accelerometer and gyroscope to detect hand orientation and motion.
- Microcontroller: Arduino Nano or ESP32 used for data acquisition.
- Bluetooth Module (HC-05/ESP32): Ensures real-time wireless data transmission.



B. Data Acquisition

Sensor data is sampled at 50 Hz and preprocessed using normalization and noise filtering. Each gesture generates a feature vector composed of flex sensor voltages and IMU readings.

Table 1: Input Features and Corresponding Output Gesture

Feature No.	Feature Name	Sensor Source	Description
F1	Flex1	Flex Sensor(Index)	Bending angle of the index finger
F2	Flex2	Flex Sensor(Middle)	Bending angle of the middle finger
F3	Flex3	Flex Sensor(Ring)	Bending angle of the ring finger
F4	Flex4	Flex Sensor(LittleFing re)	Bending angle of the Little Finger
F5	Flex5	Flex Sensor(Thumb)	Bending angle of the Thumb
A1	Accel_X	MPU6050 Accelerometer	X-axis acceleration
G1	Gyro_Y	MPU6050 Gyroscope	Y-axis angular velocity (rotation)

C. Machine Learning Model

A Support Vector Machine (SVM) classifier was trained using labeled gesture data collected from 10 users. The dataset consisted of five gestures mapped to mouse functions: move, left-click, right-click, drag, and scroll.

The classification pipeline includes:

- Feature extraction (mean, standard deviation, angular velocity)
- Label encoding
- Training and validation using scikit-learn

Table 3: SVM Input Data Table for 10 user

User ID	Flex1	Flex2	Flex3	Flex4	Flex5	Accel_X	Gyro_Y	Gesture Label
1	320	300	290	310	305	-0,12	0.15	0(move)
2	350	400	410	380	360	-0.20	0.35	1(left click)
3	340	320	300	330	310	0.10	-0,12	0(move)
4	390	410	430	400	380	-0.25	0.40	2(right click)
5	300	290	280	310	295	0.00	0.10	0(move)
6	360	375	385	370	360	0.05	-0.30	3(drag)
7	310	305	300	320	315	0.20	0.25	0(move)
8	400	420	430	410	405	-0.10	0.30	4(scroll)
9	330	310	300	325	320	0.15	-0.20	0(move)
10	355	370	380	365	360	-0.15	0.45	1(left click)

IV. Implementation and Software Design

The glove transmits data via Bluetooth to a Python-based interface on the host PC. A trained ML model receives the incoming data stream and predicts the gesture. Corresponding OS-level mouse events are triggered using the pyautogui library.

A graphical user interface (GUI) was also developed for calibration and gesture training, allowing users to customize gesture mappings[10].

```
#include <Wire.h>
#include <MPU6050.h>
MPU6050 mpu;

const int flexPins[5] = {A0, A1, A2, A3, A4};  // Flex sensors
int flexValues[5];

void setup() {
  Serial.begin(9600);      // For Bluetooth module (HC-05 or ESP32 Serial)
  Wire.begin();
  mpu.initialize();

  // Wait for IMU to initialize
  if (!mpu.testConnection()) {
    Serial.println("MPU6050 connection failed!");
    while (1);
  }
  delay(1000);
}

void loop() {
  // Read flex sensors
  for (int i = 0; i < 5; i++) {
    flexValues[i] = analogRead(flexPins[i]);
  }

  // Read IMU
  int16_t ax, ay, az;
  int16_t gx, gy, gz;
  mpu.getMotion6(&ax, &ay, &az, &gx, &gy, &gz);

  // Convert to G and deg/sec (optional scaling)
  float accel_x = ax / 16384.0;  // Convert to 'g'
  float gyro_y = gy / 131.0;     // Convert to '°/s'

  // Send data in format: f1,f2,f3,f4,f5,accel_x,gyro_y
  Serial.print(flexValues[0]); Serial.print(",");
  Serial.print(flexValues[1]); Serial.print(",");
  Serial.print(flexValues[2]); Serial.print(",");
  Serial.print(flexValues[3]); Serial.print(",");
  Serial.print(flexValues[4]); Serial.print(",");
  Serial.print(accel_x, 2);     Serial.print(",");
  Serial.println(gyro_y, 2);

  delay(100);  // Adjust for smoother output
}#include <Wire.h>
#include <MPU6050.h>

MPU6050 mpu;

const int flexPins[5] = {A0, A1, A2, A3, A4};  // Flex sensors
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  Serial.print(accel_x, 2);     Serial.print(",");
  Serial.println(gyro_y, 2);

  delay(100);  // Adjust for smoother output
}
```
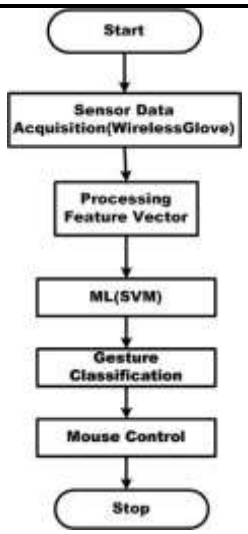

Flow Chart



V. Results

The system was evaluated for:

- Accuracy: 92.3% average classification accuracy across all gestures.
- Latency: Average system response time of 80 ms from gesture to cursor movement.
- Usability: Users reported ease of use and minimal calibration effort.

A confusion matrix revealed that most misclassifications occurred between "left-click" and "drag" gestures, which had overlapping sensor patterns.

VI. Discussion

The performance metrics validate the system's effectiveness for real-time interaction. Compared to existing solutions [3][4], our system demonstrates improved wireless efficiency and gesture recognition accuracy due to the use of SVM and sensor fusion. However, performance can degrade under excessive motion noise or inconsistent gesture execution.

Future enhancements include integrating deep learning models and haptic feedback to improve user interaction and adaptability.

VII. Conclusion

This paper presents a novel wireless glove system for controlling a virtual mouse using machine learning-based gesture recognition. With real-time responsiveness, high accuracy, and low cost, the system shows potential for widespread use in interactive computing, accessibility, and virtual environments.

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