CTS-Guard: A Wearable Smart Device for Prevention of Carpal Tunnel Syndrome

A. Sooriyakumar
Department of Computer Science & Engineering
University of Moratuwa
Moratuwa, Sri Lanka
arthikha.22@cse.mrt.ac.lk

S.J. Sooriyaarachchi
Department of Computer Science & Engineering
University of Moratuwa
Moratuwa, Sri Lanka
sulochanas@cse.mrt.ac.lk

Keywords— Carpal Tunnel Syndrome prevention, IoT, Posture monitoring, Low power consumption, Kalman filter

I. Introduction

Carpal Tunnel Syndrome (CTS) is a common repetitive strain injury caused by *prolonged wrist deviation* from non-neutral positions [1] and pressure on the median nerve. Individuals affected by CTS often experience numbness, tingling, pain, and reduced dexterity in their hands and fingers, which can significantly impact productivity in daily tasks and professional activities. In severe cases, the condition may require surgical intervention. Early detection of risky wrist postures - before permanent nerve damage occurs - is therefore crucial to prevent the onset or progression of CTS.

This paper presents CTS-Guard, a wearable that tracks wrist and finger posture, detects prolonged wrist positions, and provides real-time alerts. Unlike existing solutions focused on rehabilitation, CTS-Guard emphasizes *prevention* and ease of use.

II. Literature Review

Existing devices for preventing or managing CTS can be grouped into three main types as seen in *Table I*.

TABLE I. Comparison with Available Products

Type	Examples	Key Features	Limitations
Braces/ Splints	ErgoDrift [2]	Provide passive wrist support, reduce pain.	No active monitoring or feedback.
Reminder Apps	Workrave [3]**Error! Reference source not found.**	Alert users to adjust posture periodically.	No motion sensing; generic schedules.
Bulk Glove-based	Wearable CTS Monitor [4], DynaGaunt [5]	Measure wrist & finger motion accurately.	Bulky, uncomfortable for long use.

Prior studies on sleeve/glove-type wearables found them comfortable for normal use but highlighted preferences for smaller and lightweight wristband designs and haptic feedback [6]. Minor usability issues, such as sensor placement, were noted.

III. Materials and Methods

A. Hardware Design

The prototype (Fig. 1) is built on an *ESP32-C3* microcontroller with integrated Bluetooth-Low Energy (BLE), chosen for its low power consumption and ability to operate continuously. Two BMI160 Inertial Measuring Unit (IMU) sensors are used: one on the wrist and one on a finger (thumb, index, or middle; the prototype uses the index finger)—to track wrist and finger posture.

The ESP32-C3 is also connected to a coin - cell vibration motor for haptic feedback, powered by a 3.7 V LiPo battery with a charger module for extended use. The compact, light - weight design makes the device unobtrusive. The wrist components can be integrated into a PCB to further enhance comfort and reduce bulk for wearing during daily activities.

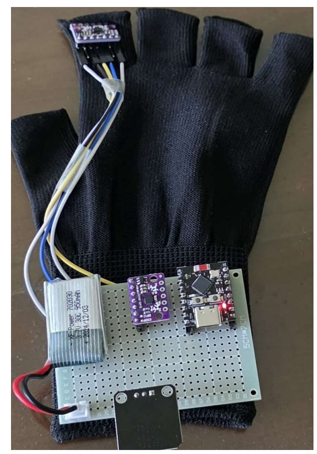

Fig. 1. Hardware prototype of the system

B. Posture Detection Algorithm

The device continuously collects raw accelerometer and gyroscope data. The ESP32-C3 measures prolonged wrist inactivity combined with repetitive finger movement against pre-defined thresholds of time. Since carpal tunnel compression is associated with improper wrist alignment that increases pressure on the median nerve [7], the algorithm evaluates both linear and angular wrist accelerations. Non-neutral wrist postures are detected by observing how the vertical gravitational acceleration ($\approx 9.8\ m/s^2$) is *redistributed across other axes* when the wrist deviates from a neutral position. However, even when the wrist remains neutral, continuous repetitive finger movement can still contribute to median nerve pressure due to muscle activity [7].

When the system detects risky posture patterns, it triggers a vibration alert prompting the user to adjust their wrist position. The alert automatically stops once wrist movement is detected. Additionally, posture data is transmitted via BLE to a mobile application, which logs the data and forwards it to a time-series database (Timescale DB) to store for further analysis.

C. *Kalman Filtering*

The Kalman filter improves the IMU signal by estimating the *true* acceleration and angular velocity while *reducing noise*. It combines each new measurement with the previous estimate, calculating each value based on their uncertainty. For stationary measurements, this allows the accelerometer axes to converge toward expected values (≈0 m/s² on X/Y and ≈9.8 m/s² on (vertical) Z), producing stable, smooth signals that enhance posture detection.

The MPU6050 was initially tested, and although it showed stable readings, its large DC offsets meant the 1-D Kalman filter mainly had to correct these shifts (Fig. 2).

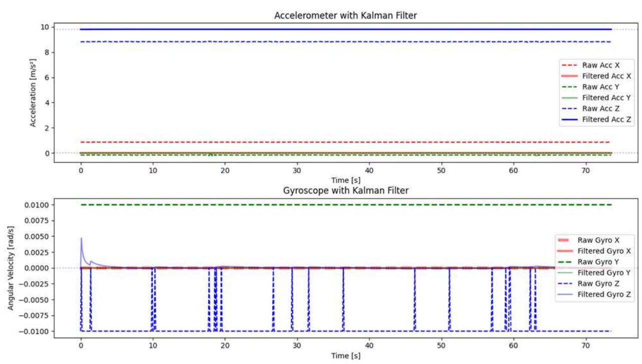

Fig. 2. MPU6050 sensor with Kalman filtering

The BMI160, however, exhibited higher sensitivity but also more noise due to quantization and sensor drift. After filtering, the BMI160 outputs showed significantly reduced noise and improved stability (Fig. 3), confirming both, its higher *sensitivity* and the effectiveness of the filtering process.

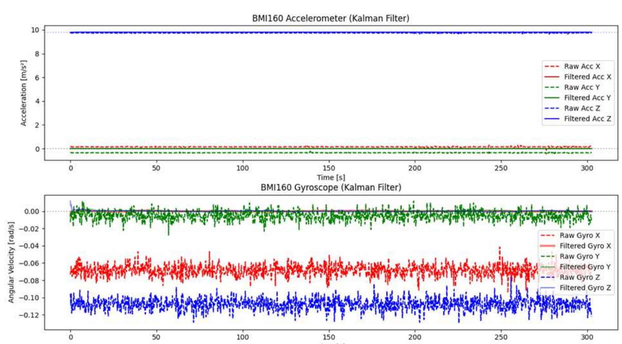

Fig. 3. BMI160 sensor with Kalman filtering

IV. Results and Discussion

A. *Performance Analysis*

The IMU signals from the wrist and finger sensors were effectively de-noised as shown in Fig. 2. and Fig. 3. The BMI160 demonstrated superior sensitivity, accuracy, and post-filter stability, while also consuming less power, making it the preferred IMU for the final system.

The prototype was further evaluated for its ability to provide corrective feedback when the wrist remained stationary beyond a pre-set threshold. Fig. 4 shows the wrist–finger resultant acceleration magnitudes alongside the vibration-motor response. The sharp spikes in wrist acceleration correspond to the user adjusting posture, which deactivates the motor, confirming reliable detection of inactivity and timely tactile feedback.

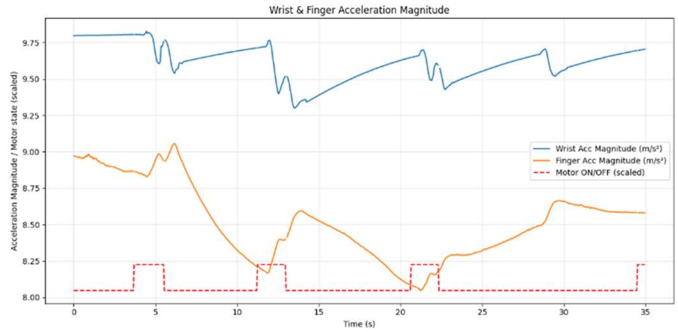

Fig. 4. Wrist, finger movement data with motor

B. *Challenges and Limitations*

Variations in typing styles (finger movement) and wrist usage patterns make it challenging to establish a universal inactivity threshold. A configuration suitable for one could falsely trigger feedback for another. Moreover, minor shifts due to strap movement or wrist shape, also affect detection accuracy.

These limitations could be mitigated in the future by fine-tuning AI models, which can adapt to individual patterns and improve overall reliability.

V. Conclusion and Future Work

This paper presents CTS-Guard, a wearable wristband that detects risky, repetitive wrist–finger postures and provides real-time alerts. The system addresses the shortcomings of braces and bulky gloves by combining comfort, continuous monitoring and low power consumption.

Future work could involve implementing an AI model trained to predict the likelihood of developing CTS. Also, integrating a PPG sensor to capture blood-flow data alongside posture information may further enhance prediction accuracy, to be validated through larger, long-term trials.

Acknowledgment

I would like to express my sincere gratitude to Dr. S. J. Sooriyaarachchi, Prof. Chathura R. De Silva, Mr. Yasantha Niroshana and Mr. Weijith Wimalasiri for their valuable guidance, constructive assistance and insights.

References

[1] K. T. Palmer, “Carpal tunnel syndrome:The role of occupational factors,” *Best Pract. Res. Clin. Rheumatol.*, vol. 25, no. 1, pp. 15–29, Feb. 2011.

[2] “Ergonomic Armrest for Office Desk – Ergodrift,” Ergotech, Mar. 2025. [Online]. Available: https://www.ergotech.fr/en/office-armrests/16-ergodrift.html. [Accessed: Sep. 29, 2025].

[3] “Welcome to Workrave – Workrave,” Workrave.org. [Online]. Available: https://workrave.org/. [Accessed: Sep. 29, 2025].

[4] M. Mack and C. -H. Min, "Design of a Wearable Carpal Tunnel Syndrome Monitoring Device," 2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS), Dallas, TX, USA, 2019, pp. 1195-1198, doi: 10.1109/ MWSCAS.2019.8884804.

[5] “DynaGaunt: What you need to know,” DynaGaunt, Jul. 20, 2024. [Online]. Available: https://dynagaunt.com/dynagaunt/ [Accessed: Sep. 29, 2025].

[6] M. Wac, R. Kou, A. Unlu, M. Jenkinson, W. Lin, and A. Roudaut, “TAILOR: A wearable sleeve for monitoring repetitive strain injuries,” in Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems, 2020, pp. 1–8.

[7] A. F. Zuniga, Carpal Tunnel Pathomechanics: Vascular Dynamics, Tissue Kinematics, & Nerve Function. Hamilton, ON, Canada, 2020.