# Extensor-C5: a Wearable for Prevention of Tennis-Elbow relapse

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***Abstract*—Tennis-elbow (lateral epicondylitis) is driven by repeated or prolonged activation of the Extensor Carpi Radialis Brevis (ECRB). Extensor-C5 is a lightweight fore-arm sleeve that fuses surface EMG with wrist-IMU data to track cumulative load on the ECRB in real-time. Six normalized factors (intensity, static hold time, activation frequency, extension strokes, wrist angle and velocity) are combined into a single risk score; LEDs, an OLED display and a vibration motor prompt the wearer to rest when thresholds are exceeded. In day-long desk tests the score stayed green (< 40 %) while heavy extension drills rapidly pushed it into orange (> 40 %) and red (> 70 %). The itsy-bitsy M4 and a 3-D-printed capsule make the device easy to reproduce and iterate. The target group is occasional athletes prone to over-use, but the method also applies to rehabilitation and workplace ergonomics.***

## I. Introduction

Lateral epicondylitis affects ≈ 1 – 3 % of adults each year and is more common in the dominant arm [1]. The pathology stems from micro-tears that accumulate in the ECRB tendon during repeated wrist extension and gripping. Commercial upper-limb wearables focus mainly on kinematics; a 2023 scoping review of 80 studies showed that IMUs were used in 84 % of designs, while only 16 % included surface-EMG [2]. By integrating EMG with motion data and a fatigue model, Extensor-C5 aims to deliver preventive feedback rather than post-injury diagnosis, bridging this technology gap.

## II. Related Work

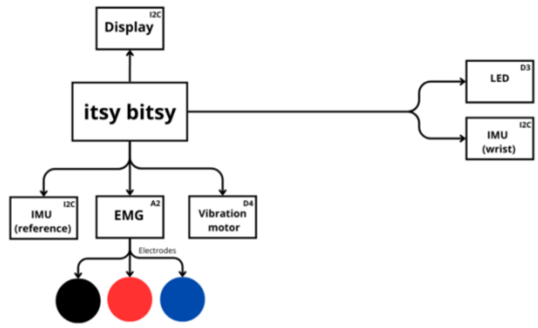
A systematic review of quantitative risk factors for elbow disorders identified high grip force, long static loads and rapid repetition as the strongest predictors of lateral epicondylitis; wrist angular velocity above 5 $^\circ\ s^{-1}$ increased prevalence by 0.10 % per $^\circ\ s^{-1}$, while awkward forearm posture (> 45 ° supination) combined with forceful lifting tripled the risk [3]. Despite such insights, no commercial band yet converts muscle-activity and kinematic data into a real-time load score with haptic warnings.

## III. Existing prototype sketches/drawings/photos

### A. The circuitboard and electronics

Figure 1 gives an overview of the signal chain. At the centre sits an Adafruit ItsyBitsy M4 Express (Cortex-M4F, 120 MHz) that is plugged into a Bitsy Expander board. The expander breaks out every pin to Grove-compatible sockets and hosts an on-board ESP32 radio module that relays Bluetooth LE packets to a companion app—no extra wiring is required for wireless communication.

*Fig. 1: Schematic overview of the hardware used for this project*




A single Grove-$I^2C$ bus fans out to three peripherals:

- a Grove - OLED Display 0.66" that shows the live risk score
- the wrist-mounted IMU (MPU-6050) that tracks extension angle and velocity
- a reference IMU on the fore-arm that cancels gross arm motion

The surface-EMG plugs into analog port A2; its differential electrodes are routed through colour-coded snap leads (black reference, red +, blue –) as shown at the bottom of Figure 1.

### B. The code and algorithm

At the start of each session a fifteen-second calibration sequence stores the resting EMG baseline and the zero-degree wrist orientation, after which the main loop begins sampling one MYOWare channel via ADC-A2 and two six-DoF frames from the wrist and reference MPU-6050s every 50 ms.

Raw EMG values are centre-aligned (|sample − baseline|) and fed through a ten-sample moving-average envelope that suppresses spike noise; an activation window opens as soon as the envelope rises 5 % above the warning limit (≈ 100 counts) and closes only after it has stayed below that threshold for 0.5 s . Within each window six primary features are accumulated such as listed in table 1. The weighted sum is the Cumulative Weighted Strain (CWS) for that window.

*Table 1: Overview of features*

| Symbol | Feature | Normalisation | Weight |
|---|---|---|---|
| $I$ | EMG intensity | / 2000 counts | 0.35 |
| $S$ | Static hold time | / 60 s | 0.25 |
| $A$ | Wrist angle | / 30 ° | 0.15 |
| $F$ | Activation frequency | / 30 $\text{min}^{-1}$ | 0.10 |
| $E$ | Extension strokes | / 1 | 0.10 |
| $V$ | Velocity | / 200 ° $\text{s}^{-1}$ | 0.05 |

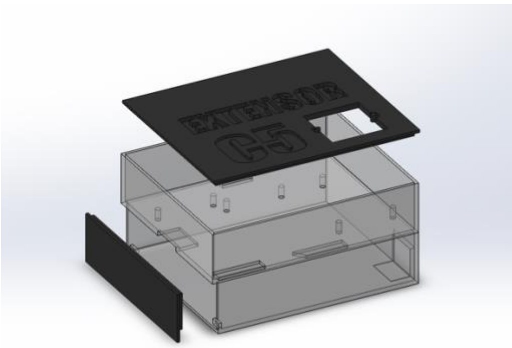
Short- and long-term fatigue are represented by a dual-time-constant "two-tank" model. The Fast integrator (20 s load-up, 45–600 s recovery) captures rapid metabolic fatigue, whereas the Slow integrator (900 s load-up, 28 h recovery) accounts for low-frequency fatigue that can last an entire day . At every control cycle both tanks move towards the current CWS in proportion to their respective time constants, and their weighted combination is forwarded to the user interface.

The resulting value is passed through a steep sigmoid so that small increases above the comfort zone provoke an immediate rise in score; green covers 0–39, amber 40–69 and red 70–100. A continuous stay in the red zone for longer than two minutes sets an over-use flag, switches the OLED to a rest countdown and tightens the warning thresholds until the cumulative load has fallen below 25 and the wrist has remained virtually motionless for thirty minutes

### C. *The capsule*

To create a protective case for the electronics and to keep the IMU at a steady place, I designed a simple capsule based on the measurement of the electronics. The capsule closes based on 0.2 mm margines so that no locking mechanism is necessary for the prototype. As seen in the figure below in the top part of the capsule is room for the display as a feedback for the user.

*Fig. 2: Solidworks assembly capsule*



### D. *The prototype*

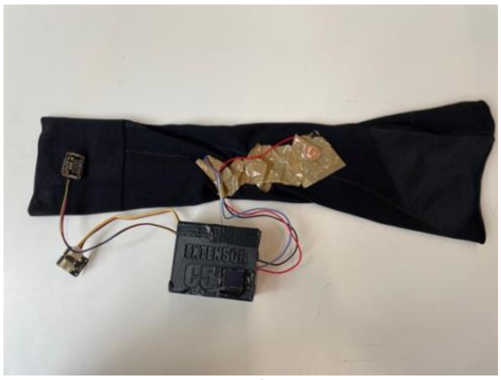


*Fig. 3: The second iteration of a wearable prototype*

The prototype itself is currently still in development, I'm working towards making the capsule smaller by reducing weight and working with a smaller expander board. A next step is improving on the materials quality and the locking mechanism with the capsule. Another point is the application on your phone where you can get an overview of the EMG data, your current score and can start the calibration process. Lastly, I aim to integrate machine learning algorithms to predict the stress on the muscle even more accurately then I do right now. Since the current calculation only partly takes personalization into account, making it vulnerable for generalization and thus inaccurate feedback

## IV. Responsible innovation

By warning *before* damage occurs, the system can reduce medical costs and lost training time. The capsule opens without screws, facilitating repair and component recycling. Future work will replace disposable electrodes with washable textile sensors and quantify the device's carbon footprint.

## V. Author bio(s) / experiences

I'm a former Business administration master that did a thesis on the implementation of wearables to support the treatment of burn-out and chronic stress. I was limitlessly passionate by the stress and how it was measured and predicted, but because of my study I had to focus on the more social part of the implementation. I wanted more, so I went to the Tudelft to learn electronics, 3D printing and machine learning to build my own wearables to predict mental health issues.

## VI. Acknowledgements

I want to thank Aardjan Van Der helm, my Digital interfaces professor, for suggesting this competition to me and motivating me to pursue my passions.

## VII. Refernces

[1] Cutts S, Gangoo S, Modi N, Pasapula C. *Tennis elbow: a clinical review article.* J Orthop. 2019; 17:203-207.

[2] Milani Zadeh S, MacDermid J, Johnson J, Birmingham TB, Shafiee E. *Applications of wearable sensors in upper-extremity musculoskeletal conditions: a scoping review.* J NeuroEng Rehabil. 2023; 20:158.

[3] Seidel DH, Ditchen DM, Hoehne-Hückstädt UM, et al. *Quantitative measures of physical risk factors associated with work-related musculoskeletal disorders of the elbow: a systematic review.* Int J Environ Res Public Health. 2019; 16:130.