Bracing Concept Proposal

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Abstract

As part of my coursework, I am developing an intelligent posture monitoring system that addresses current limitations in postural training devices. Unlike existing rigid bracing solutions, this system will use distributed sensors with magnetic attachment points to provide real-time haptic feedback. During sustained poor posture, the haptic motors will vibrate in the area of the spine that has diverged from the user's defined 'good posture'. Overtime, this will promote natural habit formation rather than forced, temporary correction.

However, I would like guidance on how this project should go (with the aim of this becoming a developed product) and would request clinical help during its development.

This proposal is presented in three distinct sections: the first will establish the project's context and review relevant literature; the second will detail the design concept, how it works, and the proposed development roadmap; and the third will request guidance on project actualization, potential clinical collaborations, and pathways for professional engagement in this field.

1 Introduction and Context

1.1 Personal Context

Reduced awareness of poor posture (and forced over-correcting at inconsistent intervals) means that over time I will be more susceptible to back pain - which is more prevalent in those suffering from adolescent idiopathic scoliosis (AIS) (An et al., 2023). Because of this, I wanted to design a product that can encourage awareness and the habitual reinforcement of good posture to encourage lifestyle changes to prevent instances of chronic pain.

1.2 Literature Review

Existing literature around this project demonstrates the considerations with machine learning for posture awareness (Shaheen et al., 2023), sensor calculations for designs (Michaud et al., 2022), and considerations of user comfort being necessary aspects of my proposed design, with how I will approach them being detailed below.

Michaud et al. (2022) demonstrated that a series of inertial measurement units (IMUs) along points of the spine was able to produce an accurate model of the spine with a "mean position error of lower than 12mm".

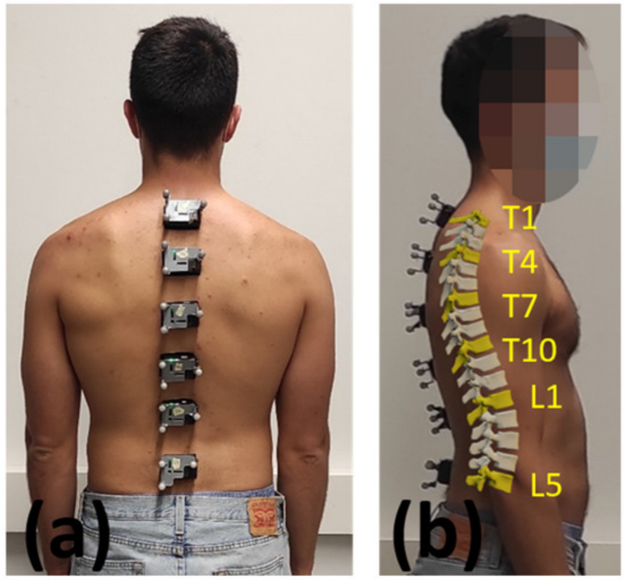

Figure 1: An image demonstrating how the sensors where distributed along the spine of this patient (Michaud et al., 2022)

The study further demonstrated the use of the multi-body model that, shown as a digital twin of the spine online, could be used to demonstrate to users quickly what it looks like to have a good posture. The software developed from this would have guidance such as tutorials for the maintenance of good posture or visualising where slouching tends to occur (to encourage, for example, the purchase of supports so that their seated posture is more comforting).

Shaheen et al. (2023) used machine learning approaches to detect Upper Crossed Syndrome using IoT sensors, highlighting the potential for automated posture classification.

A common theme throughout the literature is the lack of direct user feedback when deviating from the norm, tending to be tools to model the shape of the spine in non-invasive ways (such as through X-rays) rather than directly for the user. Therefore, I suggest the development of a posture brace that can respond to users changing posture and alert them when they are deviating.

Existing commercial posture devices typically use single-point sensing and provide binary feedback (on/off alerts), which limits their effectiveness for comprehensive spinal monitoring. This distributed sensor approach addresses these limitations by providing zone-specific feedback across multiple spinal segments, potentially improving user awareness of specific postural deviations.

2 Proposed Concept

2.1 Pseudocode

Below will be the hardware listing:

```
SENSORS:
– IMU_ARRAY[6]: Inertial Measurement Units (IMU_0 to IMU_5)
  – IMU_0: Base of spine (lumbar/sacrum)
```

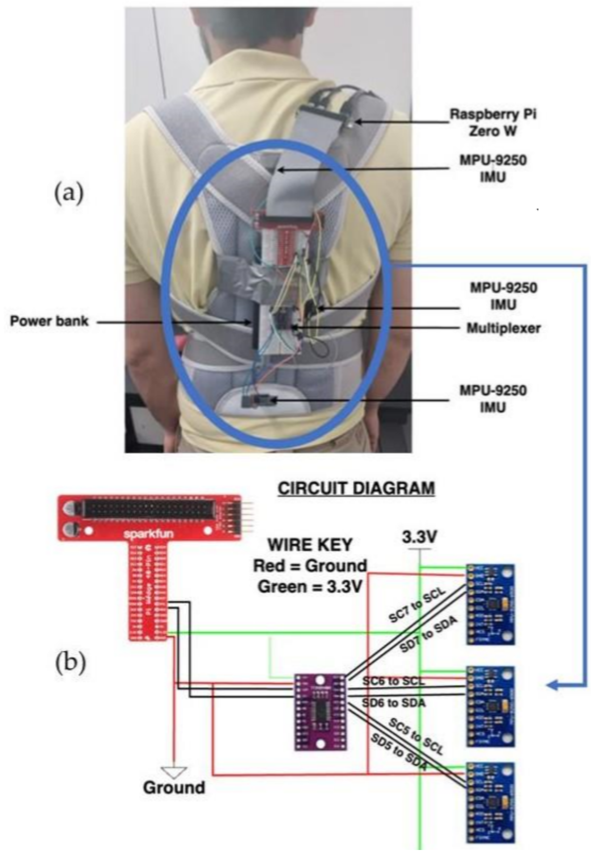

Figure 2: Electronics architecture (Shaheen et al., 2023), informing the hardware integration approach for real-time processing.

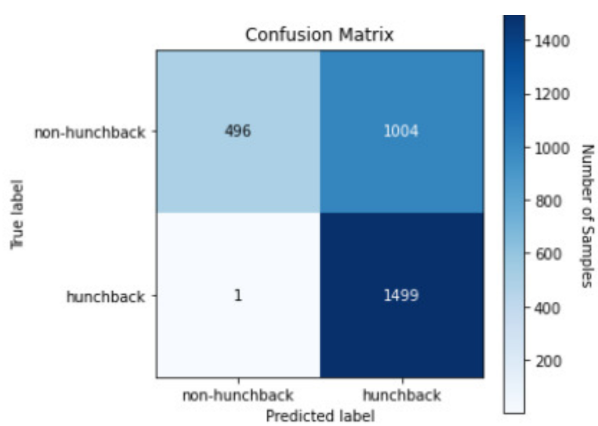

Figure 3: Confusion matrix demonstrating machine learning model accuracy for posture classification (Shaheen et al., 2023).

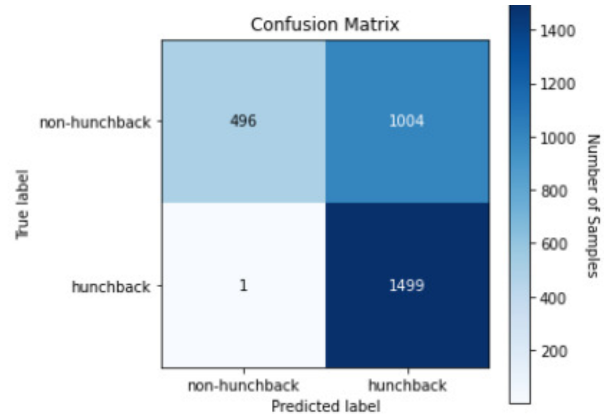

Figure 4: Confusion matrix from Shaheen et al. (2023) demonstrating 99.3% accuracy in binary posture classification, validating the effectiveness of IoT-based machine learning approaches for automated posture detection.

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    – IMU_5: Top of spine (cervical)
  – MULTIPLEXER: handles multiple simultaneous inputs of sensor data
  – VIBRATION_MOTORS[6]: Haptic feedback actuators
  – MICRO_PROCESSOR: Raspberry Pi (I/O controller, data processing & analysis)

CONSTANTS:
  – INTER_SENSOR_DISTANCE: Measured distance between sequential IMUs
  – SAMPLING_FREQUENCY: Data acquisition rate (Hz)
  – VIBRATION_THRESHOLD: Deviation threshold for motor activation
```

With the RaspberryPi, if commercialised, data can be stored locally and only the user would have access to said data. Training would still occur but would be entirely personalised.

Below is the data collection stage:

```
# these functions will be called at the sampling rate, recursively
    FUNCTION get_sensor_data():
        raw_data = [] # signifying an list
        for i = 0 to IMU_5: # iterate through each IMU
            SELECT multiplexer_channel(i)
            raw_data[i] = READ imu_orientation(IMU[i])
            # raw data will include:
            # (x,y,z) for acceleration by accelerometer
            # (XY, XZ, YZ) tilts from the gyroscope
            # example of data:
            raw_data = [(x_0, y_0, z_0, XY_0, XZ_0, YZ_0), ...]
            # function to filter data using Kalman Filter
                # as well as other algorithms to reduce the effect of drift
            RETURN filtered_sensor_data
        END
    END
```

```
FUNCTION inter_sensor_distances():
    inter_sensor_distances = []
    # ability for inputs adjacent length and angle theta
    # need to solve for calculations of distances in 3D however
    # will look into the use of LiDAR and imaging techniques to compute accurate distar

    # format of data - (x, theta)
    # x = adjacent/vertical distance between sensors in metres
    # theta = measured angle, converted to radians
    # example data below
    inter_sensor_distances = [(0.122, 1.1), (0.214, 0.87), ... ]

    RETURN inter_sensor_distances
END

FUNCTION interpret_sensor_data(filtered_sensor_data):
 # Forward kinematics using Denavit-Hartenberg parameters
 # Spline mathematics for a more apt model to interpret data from
 spine_model = calculate_joint_angles(filtered_sensor_data)

 # Compare against baseline "good posture" profile
 deviations = []
 for i in range(6):
     if abs(spine_model[i] - baseline[i]) > VIBRATION_THRESHOLD:
         deviations.append(i)

 RETURN spine_model, deviations

 FUNCTION control_haptic_feedback(deviated_sensors):
 while True:
     send a signal to the channel that contains the deviated sensor
     this triggers the corresponding motor

 END
```

2.2 Electronics

ELECTRONICS: - IMU: MPU-6050 (6-axis, I2C communication) - Vibration Motors: Coin-type, 3V, 80mA - Processing: Raspberry Pi Zero W (WiFi capability for updates and potential for computational expansion (e.g. machine learning)) - Power: Rechargeable battery system - Attachment: Magnetic coupling - magnets on the the senor and sheet for connections

2.3 Phase 1 Goals

For this month: - Validate sensor accuracy with basic tests - Basic forward kinematics calculations and understanding manipulation of serial data to program a reaction if surpassing a degree of threshold - Representing the spine as a basic spline

3 Guidance for future collaboration

I am seeking clinical mentorship to validate this concept's foundation. Specifically, I require guidance on: (1) existing clinically-validated postural parameters and deviation thresholds, (2) appropriate patient safety protocols for prolonged haptic stimulation - or adjustments to this concept surrounding user safety, and (3) pathways for medical device development.

I am available full-time over the summer holidays (July - August 2025) and have sensor validation the first draft prototype scheduled for completion by July 2025.

4 Conclusion

This adaptive posture monitoring system addresses critical gaps in current postural training devices through distributed sensing, real-time haptic feedback, and personalized learning algorithms. The proposed system offers continuous monitoring without restrictive bracing, potentially reducing long-term back pain development in AIS patients and improving postural habits in general populations. Clinical collaboration will be essential for validating its efficacy and ensuring patient safety protocols and I will be grateful at any avenue for collaboration.

5 References

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Michaud, F., Lugrís, U., Cuadrado, J. (2022). Determination of the 3D Human Spine Posture from Wearable Inertial Sensors and a Multibody Model of the Spine. Sensors, 22(13), 4796. https://doi.org/10.3390/s22134796

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