Bracing Concept Proposal

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Abstract

This project proposes 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'. Over time, this will promote natural habit formation rather than forced, temporary correction.

However, the authors seek 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 Literature Review

AIS affects 0.475.2% (An et al., 2023) of adolescents globally. It can have long-term consequences ranging from physical discomfort to psychological effects like reduced self-esteem. Though often mild, the condition can worsen if left unchecked. Similarly, Upper Crossed Syndrome (UCS) -a muscular imbalance commonly seen in both young adults and older populations- is strongly linked to chronic neck and upper back pain. A review by Nijs et al. (2007) describes how UCS is frequently overlooked despite its high prevalence in individuals with sedentary lifestyles or postural irregularities, and it often leads to long-term discomfort and functional limitations. These patterns suggest that posture-related issues affect a broad portion of the population and are not limited to students or office workers.

Technological interventions aimed at improving posture are becoming increasingly relevant in both medical and consumer spaces. Michaud et al. (2022) demonstrated that using a series of Inertial Measurement Units (IMUs) along the spine can generate an accurate 3D model of spinal posture with a mean position error under 12mm. Their study highlights the potential of creating a digital "twin" of the spine, which could be visualised through apps to help users see how their

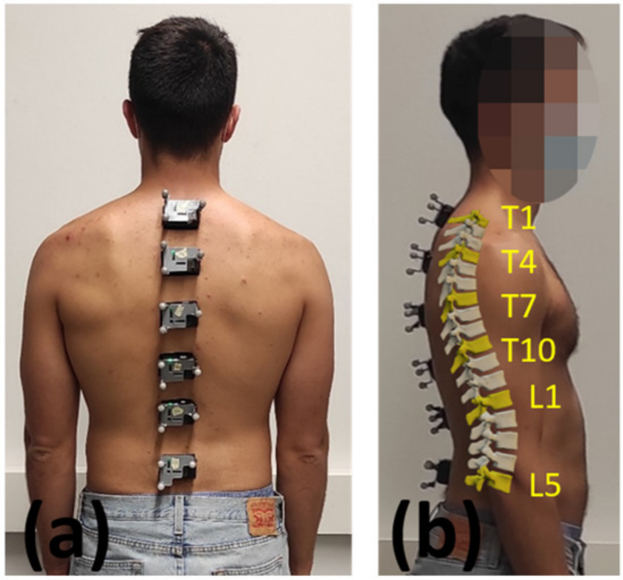

Figure 1: An image demonstrating how the sensors are distributed along the spine of this patient (Michaud et al., 2022)

posture deviates and learn how to correct it. Similarly, Shaheen et al. (2023) explored the use of machine learning with Internet-of-Things (IoT) sensors to classify posture disorders like Upper Crossed Syndrome. These innovations show promising pathways for using technology to monitor and improve posture, but a common limitation across current approaches is their passive nature: they often lack real-time, user-specific feedback.

This system addresses these limitations by introducing distributed haptic feedback that activates when one's posture exceeds defined thresholds. The aim is not to enforce perfect alignment constantly but to encourage a habit of gentle correction and bodily awareness. This method is backed by psychological models such as Self-Determination Theory, which argues that giving users autonomy -by allowing them access to data and non-invasive feedback- fosters more meaningful, long-term habit change. A review by van der Weegen et al. (2021) confirms that wearables with active feedback and behaviour-tracking features are more effective than those offering only passive monitoring. Therefore, a system that gently prompts the user while also helping them visualise their spinal alignment could lead to more sustainable behavioural shifts in posture than static braces or simple alert-based devices.

1.2 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)
    – IMU_5: Top of spine (cervical)
  – MULTIPLEXER: handles multiple simultaneous inputs of sensor data
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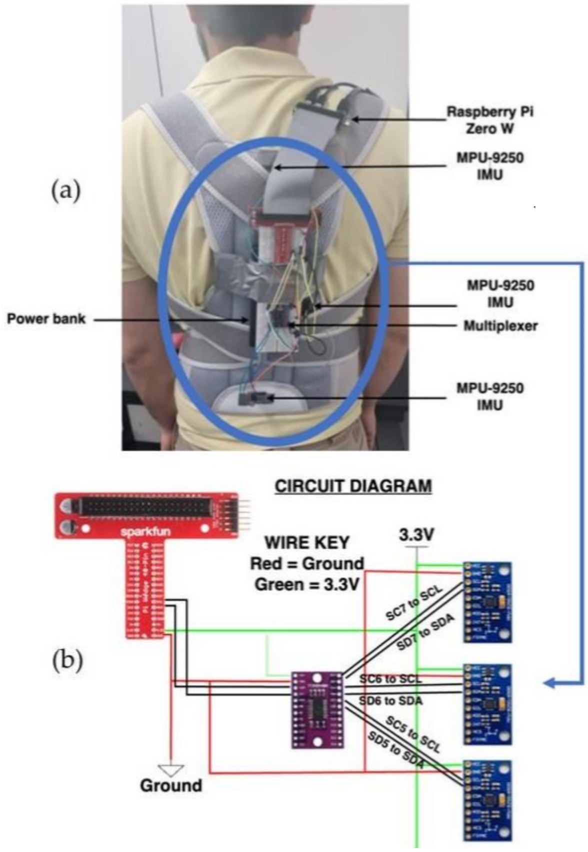

Figure 2: Electronics architecture (Shaheen et al., 2023), informing the hardware integration approach for real-time processing.

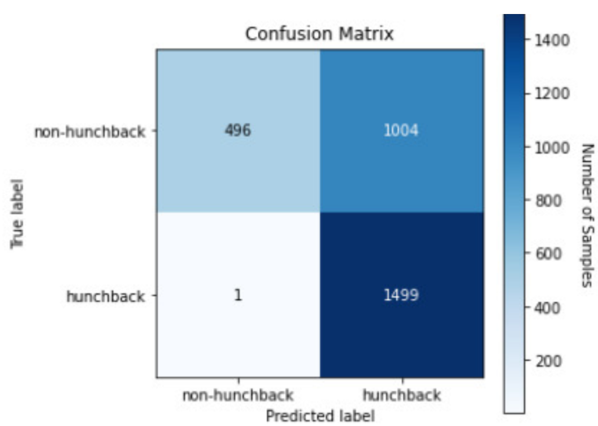

Figure 3: Confusion matrix from (Shaheen et al., 2023) demonstrating 99.3% accuracy in binary posture classification, validating the effectiveness of IoT-based machine learning approaches for automated posture detection.

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  – 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 Raspberry Pi, data storage remains local, ensuring user privacy and data ownership. 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():
    filtered_data = []  # list to store processed sensor readings

    FOR i = 0 TO 4:  # iterate through 5 IMUs (indexed 0-4)
        SELECT multiplexer_channel(i)

        # Read raw data while this IMU is selected
        accel_reading = READ accelerometer(IMU[i])  # (ax, ay, az)
        gyro_reading = READ gyroscope(IMU[i])       # (gx, gy, gz)

        # Process data immediately while channel is active
        sensor_data = combine_readings(accel_reading, gyro_reading)

        # Apply Kalman filter and sensor fusion to this sensor's data
        filtered_reading = apply_sensor_fusion(sensor_data, previous_state[i])
        filtered_data.append(filtered_reading)

        # Update state for next sampling cycle
        previous_state[i] = filtered_reading

    END FOR

    RETURN filtered_data  # Returns 5 processed orientation vectors
END FUNCTION

FUNCTION inter_sensor_distances():
    inter_sensor_distances = []

    FOR i = 0 TO 3:  # 4 links between 5 sensors
        # Distance magnitude remains fixed (measured during calibration)
        link_length = STORED_DISTANCES[i]  # e.g., [0.122, 0.214, 0.18, 0.15]
```

```
        # Current angle between adjacent sensors (this varies in real-time)
        current_angle = calculate_angle_between_sensors(sensor_orientation[i], sensor_orie

        # Store as (fixed_distance, current_angle) for forward kinematics
        inter_sensor_distances.append((link_length, current_angle))
    END FOR

    RETURN inter_sensor_distances  # [(d01, theta_01_current), (d12, theta_12_current), ..
END FUNCTION

   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
```

1.3 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

1.4 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

2 Guidance for future collaboration

This project requires guidance in three specific areas: (1) validation of clinically-accepted postural deviation thresholds and measurement protocols used in current practice, (2) established safety guidelines for prolonged haptic stimulation, including duration limits and intensity parameters, and (3) pathways for medical device development, to validate this measurement approach against established postural assessment methods (such as the Cobb angle) and to ensure the feedback mechanisms (haptic feedback) aligns with existing physiotherapy protocols.

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

2.1 Clinical Measurements of Outcomes

In a clinical context, assessing the efficacy of the wearable system will go beyond the subjective user feedback: a time-normalised scoring system could be implemented to evaluate how often the user maintains correct posture within a set period. Furthermore, introducing a 'Corrective Event Ratio' (CER) measuring the frequency of haptic interventions per hour could provide a robust metric of user improvement. This would be supplemented by pre- and post-intervention postural photography and clinical evaluations (e.g. shoulder symmetry, spinal alignment). Physiotherapists can track spinal curvature progression using standard metrics while correlating it with the data provided by the device in advanced applications. Future versions could incorporate surface EMG sensors to assess muscular activation improvements.

2.2 Ethical Considerations

From an ethical standpoint, the system is designed to encourage behavioural change through gentle, non-invasive reminders rather than discomfort or pain. The vibration feedback is intentionally low intensity to avoid anxiety, especially for neurodivergent users. Users would have the ability to customise feedback intensity or disable it temporarily in sensitive contexts. False positives and negatives are anticipated and mitigated through calibration and machine learning algorithms, but further safety layers will be researched to prevent harmful posture corrections (e.g. when a user leans due to medical necessity or fatigue).

The system will also include hard limits to ensure the haptic motor cannot activate for longer than a few seconds continuously. Consent, privacy, and data transparency will be emphasisedno user data is stored or transmitted without explicit permission. In clinical trials, participants retain full withdrawal rights, and younger users will be provided with age-appropriate explanations to avoid excessive monitoring that may cause body image anxiety.

2.3 Clinical & Commercial Applications

2.3.1 Clinical Applications

Clinically, the wearable can support posture retraining programs supervised by physical therapists. It may also be used as an adjunct to postural correction braces, encouraging compliance by alerting users before significant deviations occur. Data gathered from the system can inform remote physiotherapy or telerehabilitation consultations. Its role in neurological rehabilitation (e.g., post-stroke, Parkinson's disease) or surgical recovery protocols further expands its potential. The device may eventually become a standard component in adolescent scoliosis management or postural kyphosis treatment plans.

2.3.2 Commerical Applications

The system is positioned for use in preventative health and lifestyle markets. Potential users include teenagers, office workers, and gamersdemographics known to spend extended periods in sedentary positions. A mobile app will accompany the wearable, offering gamified elements like posture streaks, a posture score, and progress tracking graphs. Integration with existing health ecosystems like Apple Health or Fitbit could provide users with a holistic view of their musculoskeletal health. Retail pathways may include ergonomic stores, physiotherapy clinics, and consumer electronics outlets. A subscription-based coaching feature may also be introduced.

3 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 we will be grateful at any avenue for collaboration.

4 References

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