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Head Movement in Task Analysis

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Abstract

Context awareness opens a new range of potential applications for dynamic interaction with computers. **This project has shown that using inertial sensors in a wearable device can passively recognise human activities.** Tracking of head movement allows prediction of basic "sedentary" activities, task transitions and cognitive load. This novel system shows promising performance on the dataset of twenty people.

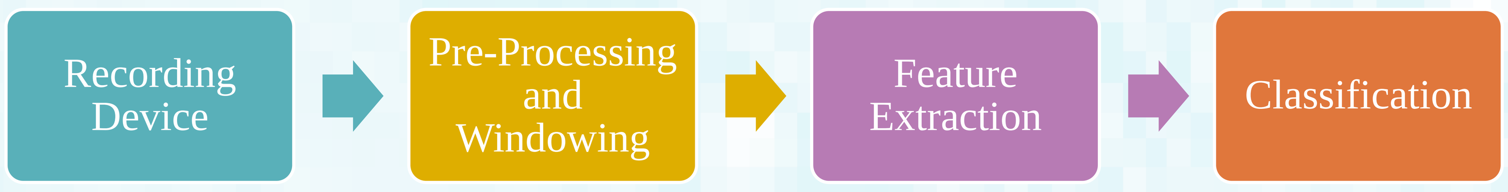

Figure 1: System Architecture

Recording Device

The recording device contains: an Inertial Movement Unit (3 axis accelerometer, gyroscope and magnetometer), Arduino microcontroller, Bluetooth and a battery.

Figure 2: One of the twenty experimental participants with the head and hip devices

Experiment Design

The experiment consisted of four parts:

1) Calibration and Familiarisation
2) Six basic activities (Reading, Rubik's Cube, Walking, Watching, Writing, Talking)
3) Arithmetic tasks of three difficulty levels to simulate cognitive load
4) Free activity for 10 minutes (real world simulation)

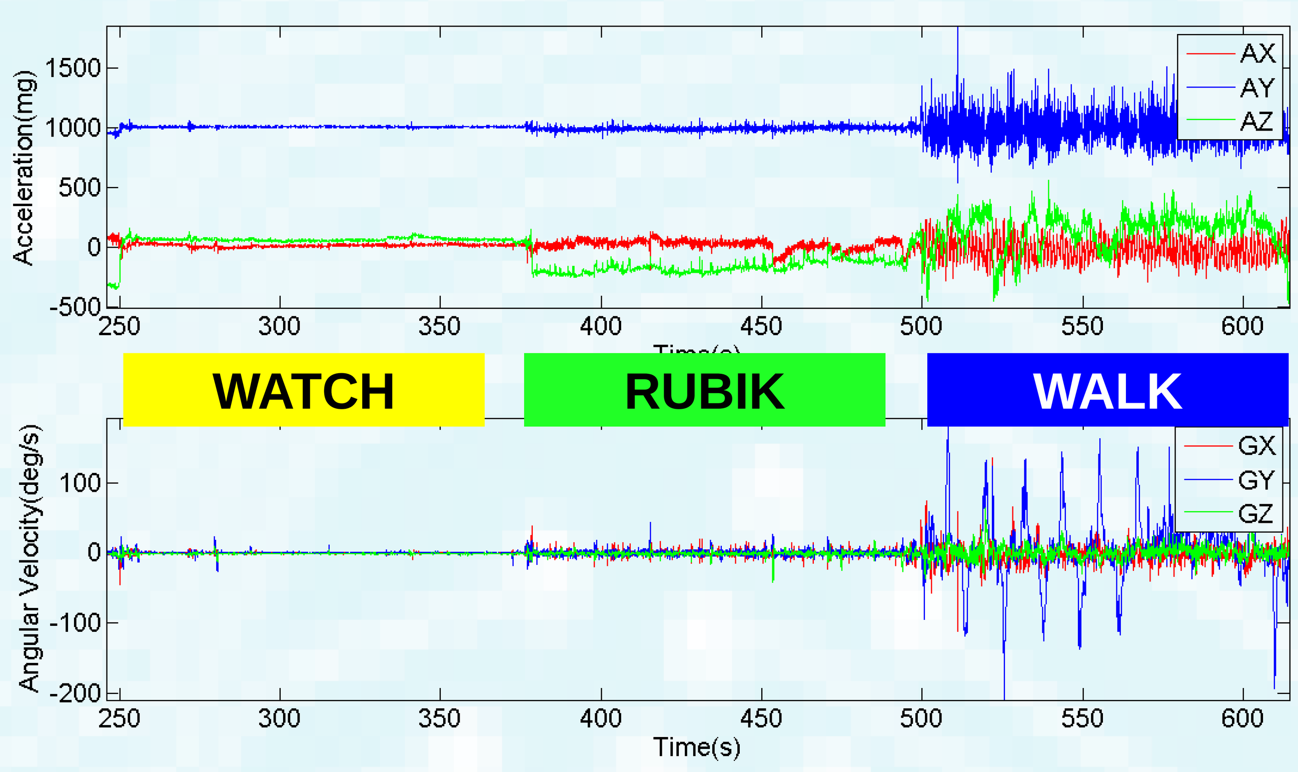

Figure 3: Example of Measured Data for three activities (Top: Accelerometer, Bottom: Gyroscope)

Pre-processing and Head Tracking

The signals were synchronised, scaled and then filtered using median and digital filters. The head tracking algorithm of sensor fusion corrects errors in position estimation using a feedback loop of gravity:

$$\begin{pmatrix}\theta_x\\ \theta_y\\ \theta_z\end{pmatrix}_k = \begin{pmatrix}\theta_x\\ \theta_y\\ \theta_z\end{pmatrix}_{k-1} + \begin{pmatrix}g_x\\ g_y\\ g_z\end{pmatrix}\Delta t + K_p(\tilde{a}\times\tilde{d})$$

where: Θ: orientation angle, g: gyroscope
a: acceleration, t: time, K is controller constant, and
d: current orientation estimate of direction of gravity

The signals are segmented into one second windows.

Feature Extraction

Statistical characteristics were extracted from the windows. Twenty features were chosen to give deterministic power over classifying each outcome (E.g. mean gyroscope jerk, acceleration 90% percentile)

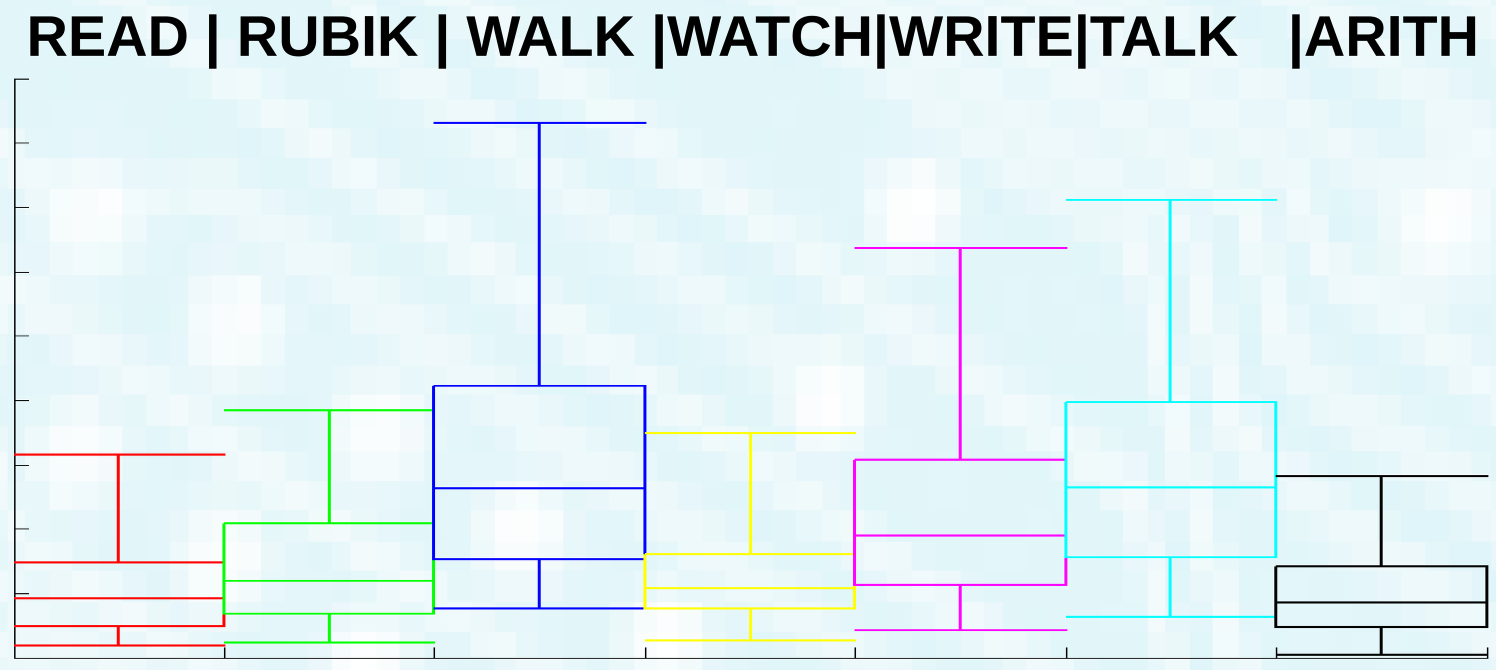

Figure 4: Normalised Box Plot Feature Distribution for seven activities - Acceleration 10% percentile value for window

Classification and Results

A variety of classifiers were tested and evaluated over the seven activity dataset. There was some subject variability.

Nearest Neighbour: 83% accuracy *(Cross Validation)*
Decision Tree (J48): 76% accuracy *(Cross Validation)*
Bayesian 42% accuracy *(Cross Validation)*

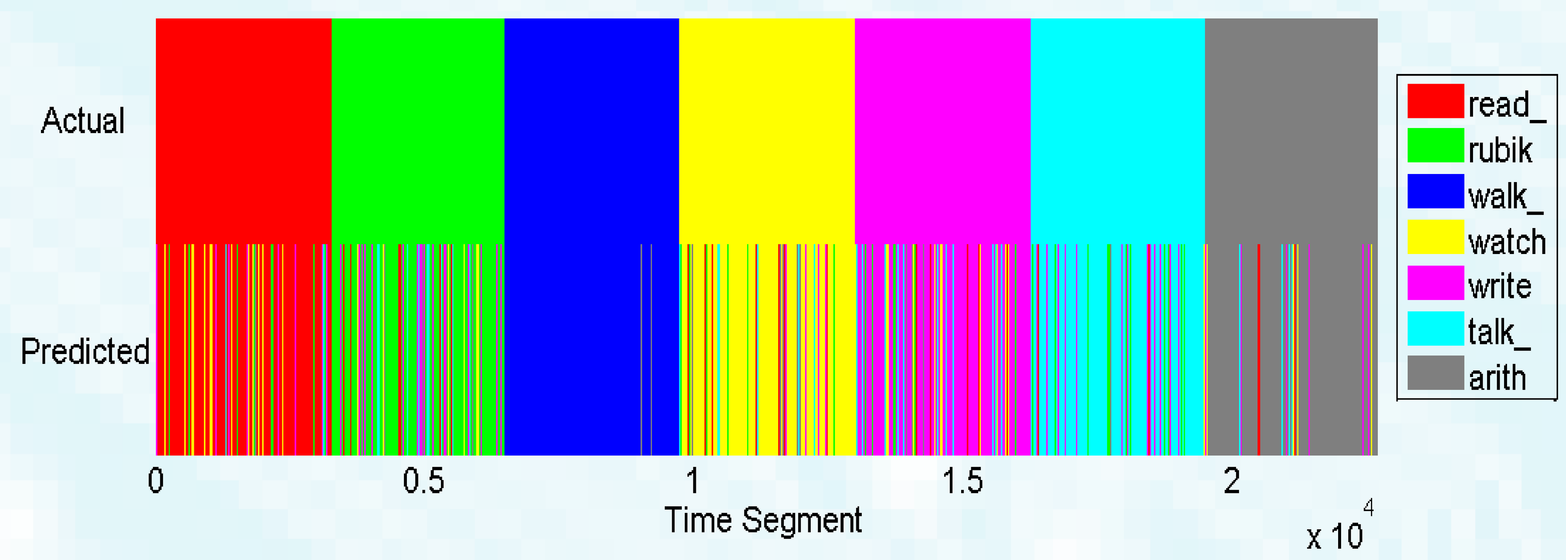

Figure 5: Nearest Neighbour Classification results for the seven activities group dataset

Cognitive Load

Cognitive Load is the amount of working memory involved in completing a task. This is a measure of how much mental effort a task is taking. The hypothesis is people externalise their thought processes through subtle unconscious head movements. Here's an example of three levels of load:

L1: 13 + 4 = ?
L4: 55 + 26 = ?
L7: 735 + 498 = ?

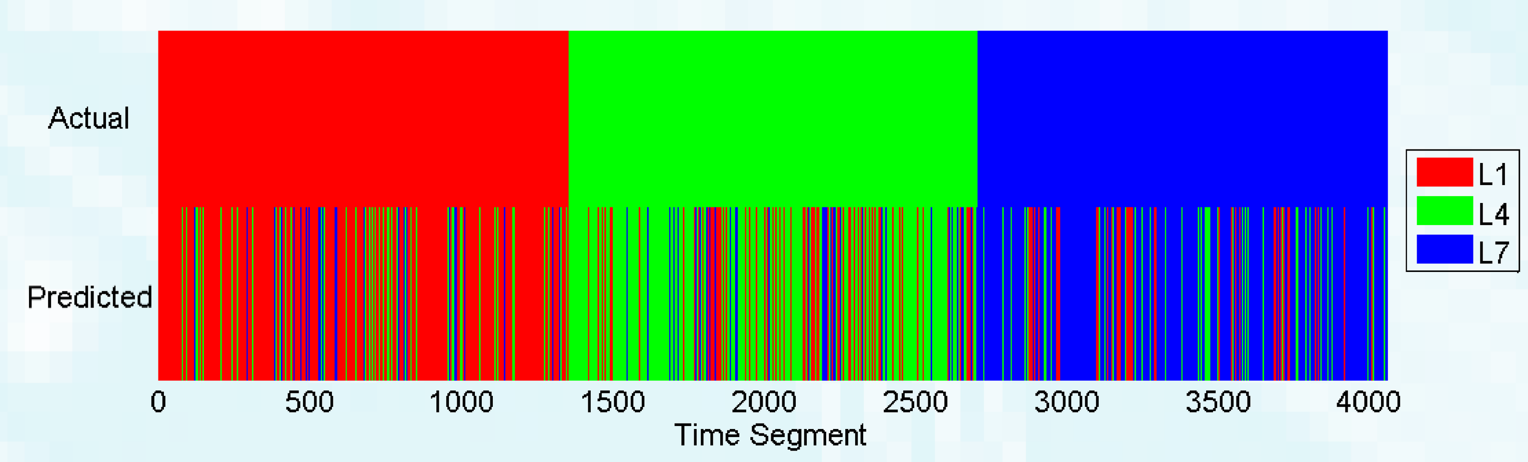

Figure 6: Classification results for the cognitive load.
Nearest Neighbour: 71% accuracy (Cross Validation)

Discussion & Conclusion

The novel method of using head tracking to distinguish mostly stationary activities had a classification accuracy of 83%. Similar studies achieve similar accuracies but with more sensors and more physical tasks. Combination with other sensors, real time processing and adaptation to real world environments are areas for improvement. Potential applications include interactive learning, wearables, employee monitoring in high stress jobs and e-assistance.

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