CMP:6046B – Ubiquitous Computing

A3/A4 Lab Reports

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<u>A3 – Activity Recognition</u>

1: Raw Data Plot Analysis

Raw sensor data collected from smartphones accelerometer and barometer provides insights into different physical activities. After some data processing, three key measurements are visualized:

- Accelerometer Magnitude: The top plot shows overall magnitude of acceleration across all three axes. This provides a measure of intensity the movements made during different activities
- Barometric Pressure: The middle plot shows pressure readings after smoothing, the sensor detects changes in elevation, which is crucial in distinguishing between activities with vertical movement
- Activity Labels: Shows which activity is what by following activities indexing:

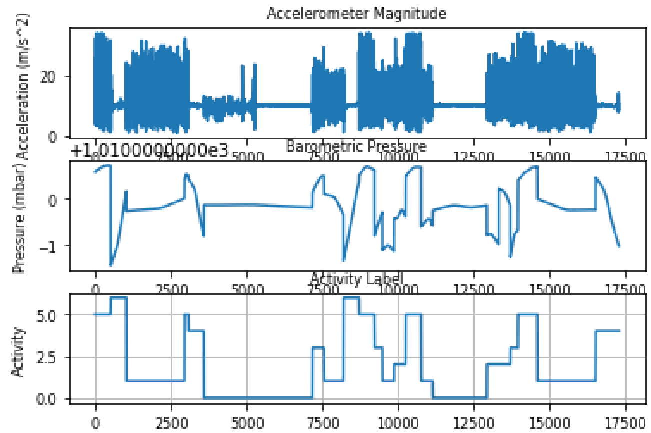


Figure 1: Raw Data

```
# Index for each activity
activity_indices = {
  'Stationary': 0,
  'Walking-flat-surface': 1,
  'Walking-up-stairs': 2,
  'Walking-down-stairs': 3,
  'Elevator-up': 4,
  'Running': 5,
  'Elevator-down': 6
}
```

Figure 2: List of classifications

2/3: Extracted Feature Analysis

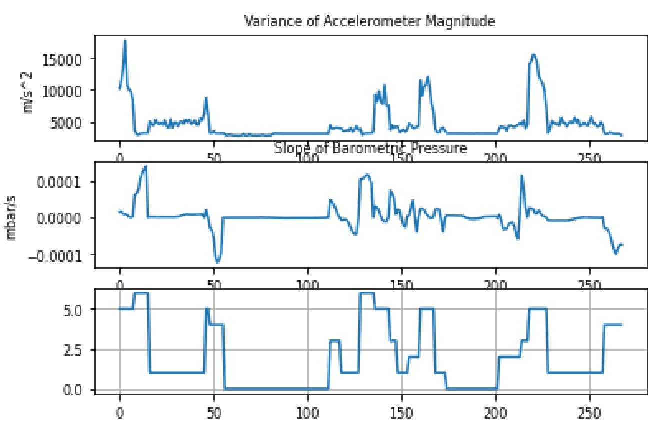


Figure 2: Feature Data

High peaks correspond to running, creating large variations in acceleration due to intensity and impact of running movements

Values at timestamp 25-50 shows moderate, consistent variance in acceleration, representing walking

Near-zero regions indicates stationary periods where minimal movement occurs

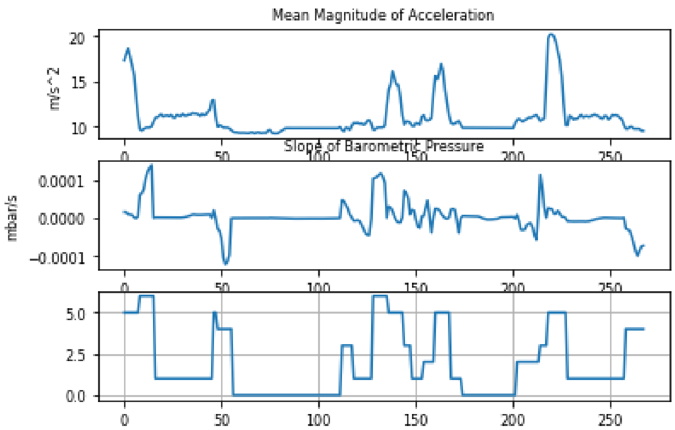


Figure 2.1: Mean magnitude of acceleration

Peaks at timestamp 10 and 210 shows running, with highest mean acceleration - loose pocket allows more dramatic phone movement during high impact activities

Near-zero regions at timestamp 75-100 indicate stationary periods, as even in the loose pocket the phone experiences the same minimal (next-to-none) movement when still

Irregular peaks at timestamp 150-175 reveals stair activities, loose pocket causing more erratic variance during stair movement

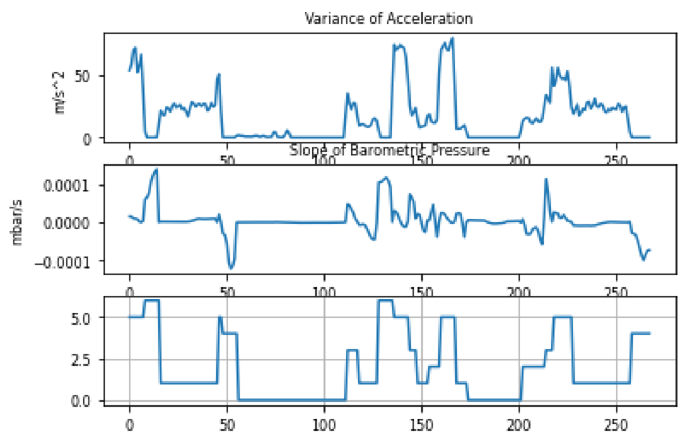


Figure 2.2: Variance of Acceleration

Running distinctively shown by highest mean acceleration values at 18-20m/s^2,

Stationary activity maintains values of 9.8 m/s^2, gravitational pull on earth from timestamps 75-100, reliable regardless of pocket placement

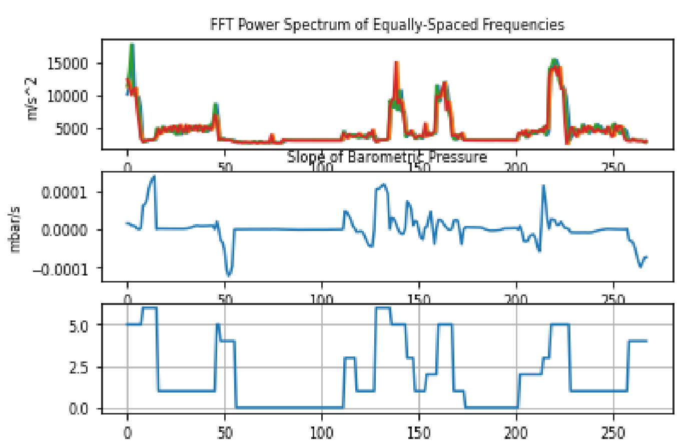


Figure 2.3: FFT Power Spectrum of Equally-Spaced Frequencies

Running at timestamps 10-210 is characterised with higher power across multiple frequency bands

Walking activities show moderate consistent power in lower frequency bands, correlating to normal walking rhythm

Stationary periods and elevator movements show low frequency content, even in a loose pocket the little movement in these activities

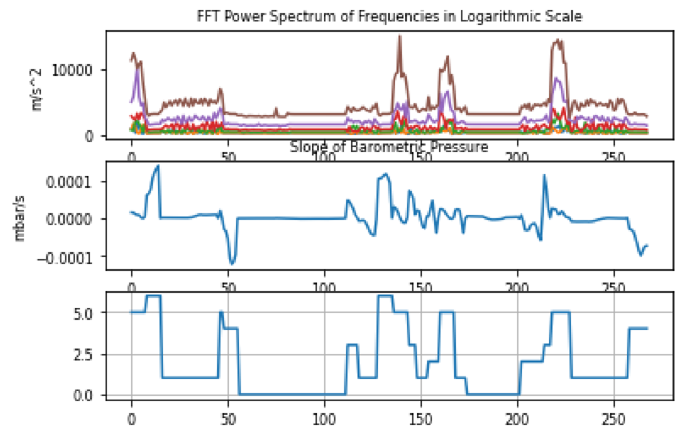


Figure 2.4: FFT Power Spectrum of Frequencies in Logarithmic Scale

Logarithmic scaling highlights differences in frequency patterns

Running shows significant power across multiple frequencies prominent to other activities due to faster movements, amplified by the loose pocket

Stair activities display complex patterns due to mixed movements (vertical & horizontal)

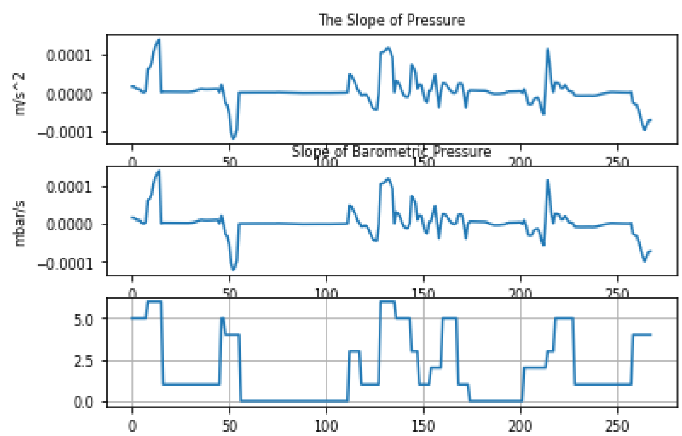


Figure 2.5: Slope of Pressure

Elevator movements clearly identified by consistent pressure slopes: positive for elevator going up (timestamp 125) and negative for elevator going down (timestamp 50 and 250), sensor unaffected by loose pocket placement

Stair activities at timestamp 150-175 shows step patterns, with small plateaus corresponding to the landings, reliable vertical movement despite phone placement

Activities without vertical movement all show flat-zero

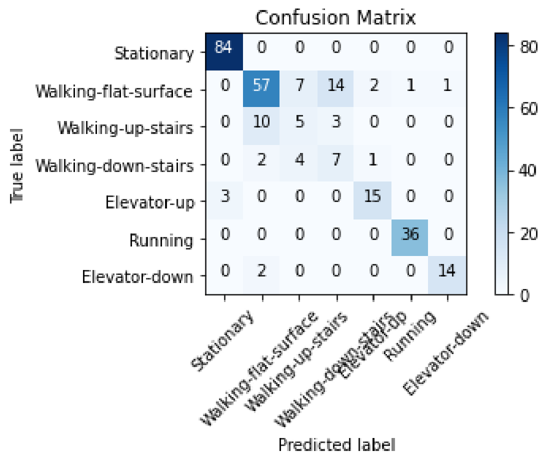
Data collection considerations:

Several factors during data collection influenced the quality and characteristics of the sensor readings

- Phone placement: smartphone was placed in a loose pocket, which has effects on sensor readings
    - Loose pocket allows for more freedom of movement, potentially introducing extra noise that may have impacted readings
    - Inconsistencies in phone orientation
    - Higher variable acceleration than a more secure pocket would
    - Impact forces (walking/stairs) may be dampened due to the phone moving in the pocket
- Stair configuration - stairs used for data collection had landings where walking on flat surfaces occurred
    - Mixed patterns in walking up/downstairs as a result
    - Brief periods of flat walking

- Barometer shows plateaus during these landing areas on the stairs

4. Confusion Matrix (own data)



Precision= TP / (TP + FP)

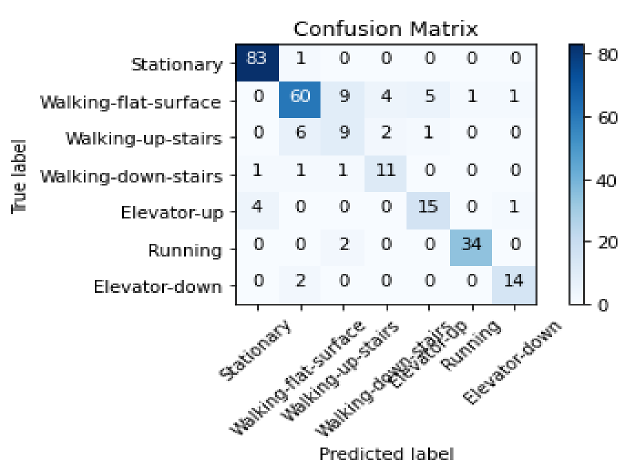
Recall = TP / (TP + FN)

Accuracy = (TP / TN) / (TP + TN + FP + FN)

Activity	Precision	Recall	Accuracy
Stationary	96.55%	100%	98.88%
Walking-flat-surface	80.28%	69.51%	85.45%
Walking-up-stairs	31.25%	27.78%	91.04%
Walking-down-stairs	29.17%	50.00%	91.04%
Elevator up	83.33%	83.33%	97.76%
Running	97.30%	100%	99.63%
Elevator-down	93.33%	87.59%	98.88%

Overall accuracy = 81.66%

5. Confusion Matrix (with training/test data)



Activity	Precision	Recall	Accuracy
Stationary	94.32%	98.81%	97.76%
Walking-flat-surface	85.71%	75.00%	88.81%
Walking-up-stairs	42.86%	50.00%	92.16%
Walking-down-stairs	64.71%	78.57%	96.64%
Elevator up	71.43%	75.00%	95.90%
Running	97.14%	94.44%	98.88%
Elevator-down	87.50%	87.50%	98.51%

Overall accuracy = 84.33%

<u>Comments</u>

Overall performance:

- The generalised model achieved a slightly better overall accuracy rating (84.33% vs 81.66%), suggesting that incorporating data from multiple users creates a more robust classification model
- This small improvement (2.67%) indicates that while personal variation exists, the patterns of different activities are consistent enough across individuals to be recognised

Activity-Specific Observations:

Stationary

- Both models perform well on stationary detection – minimal movement during this activity results in higher accuracy in sensing

Walking-flat surface

- The generalised model shows improvement in precision (85.71% vs 80.28%) but lower recall (75.00% vs 69.61%) – suggesting that with more diverse training data, the classifier becomes more selective about what it labels as walking, resulting in fewer FP's but potentially missing walking instances

Walking-upstairs/Walking-downstairs

- Most dramatic improvement is seen in walking-down stairs, where precision increased (69.71% vs 29.17%) – this suggests that stair climbing patterns vary considerably between individuals, and the trained model captures these variations better – the phone placement in a loose pocket likely contributed to inconsistent readings during stair activities, but the diverse training data helped overcome this

Elevator Movements

- Both models performed well on elevator detection, the distinctive vertical movement pattern captured by the barometer seems consistent regardless of individual differences – generally people all used the same elevator which may also allude to the high precision

Running

- Running recognition remains highly accurate in both models, with the person-dependent model showing slightly better recall (100% vs 94.44%) – the high intensity, distinctive motion of running makes it easily distinguishable regardless of individual variation

Implications

- Activities with distinctive sensor identifications (stationary, running, elevator movements) are well recognised by both models
- Complex activities benefited from the diverse training data – generally improving precision, accuracy and recall
- The model trained on other user data handles the variability introduced by the loose pocket placement, suggesting robustness in the trained model

6: Top Feature identification

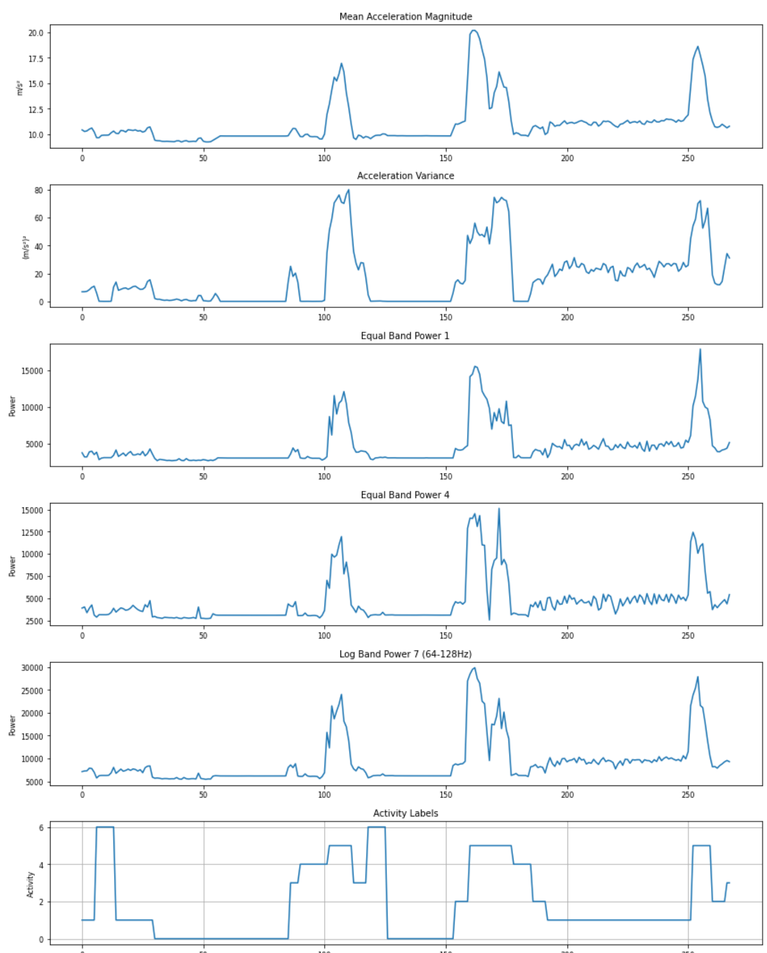


Figure 3: Top feature plots with activity labels

Mean Acceleration Magnitude

- Graph clearly shows distinct patterns of different activities – running at timestamps ~160 and ~260 showing highest values (~20m/s^2)
- Walking-up stairs at timestamp ~105 shows moderate-high values (~15m/s^2)
- Stationary activities show baseline values (9.8m/^2) – Gravitational pull
- Clear notable differences makes this feature reliable for distinguishing between activities

Acceleration Variance

- Dramatic differences between activities – highest values (~70-80m/s^2) for walking up-stairs at timestamp ~105 and running at timestamp ~160
- Near-zero values during stationary periods
- Moderate, sustained variance for walking-flat surface at timestamps ~200-250
- Loose pocket placement amplifies these differences, phone moves more freely during high-impact activities
- Stark contrasts explain why this feature is discriminative for activity classification

Equal Band Power 1

- Captures fundamental movement patterns in lowest frequency range
- Critical for distinguishing rhythmic activities (walking) from non-rhythmic ones (stationary)
- Less affected by loose pocket placement than higher frequency bands

Log Band Power 4

- Captures rapid movement and impacts primary during running and stair activities
- Complements low frequency information by capturing different aspects of the movement patterns

Log Band Power 7 (64-128Hz)

- Represents highest logarithmic frequency band
- Captures very rapid, short duration movements and impacts – perfect for running
- Loose pocket placement introduces noise during high-impact activities

7: New Experimental Features

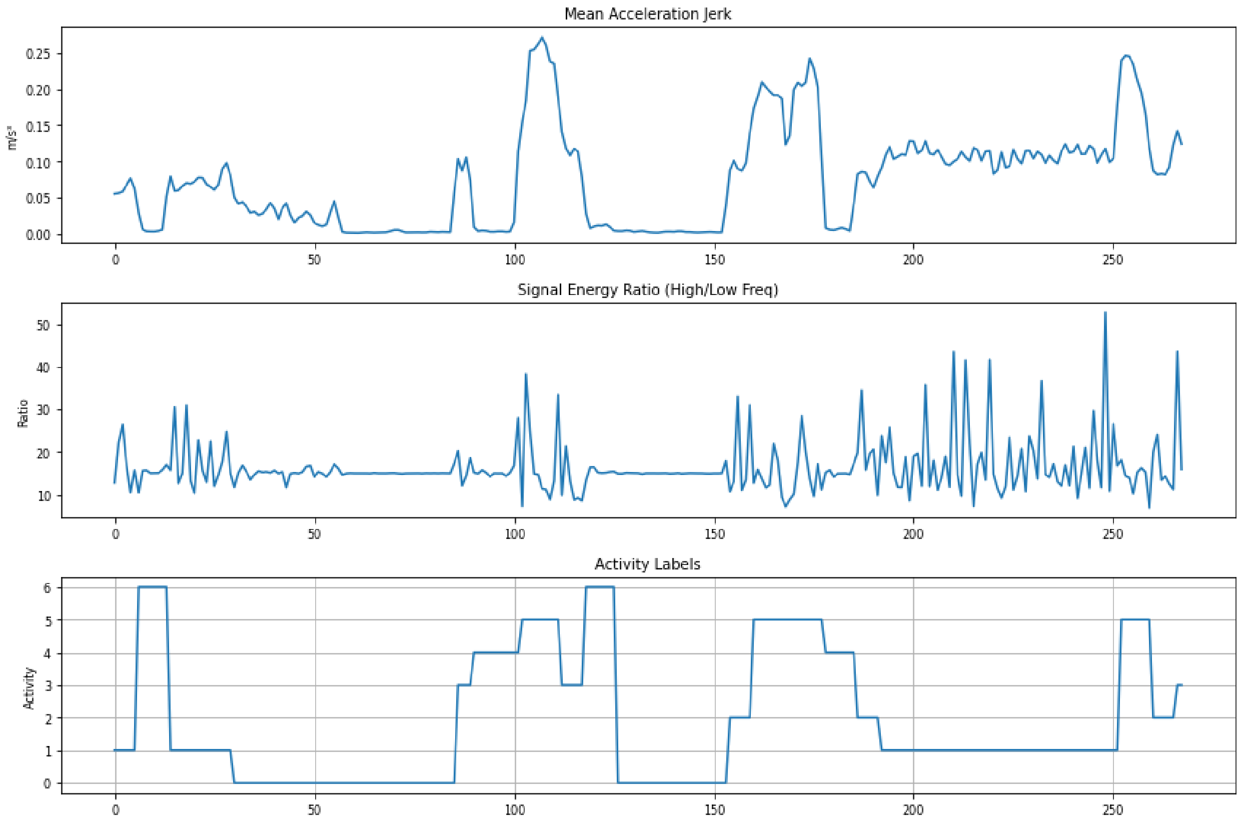


Figure 4: Newly Extracted feature time-series plot

Rationale

1. Acceleration Jerk

Physical basis: Jerk measures how rapid acceleration changes over time(the derivative of acceleration). While acceleration shows how quickly velocity changes, jerk captures the smoothness of those changes.

Why it's effective for activity recognition:

- Different activities produce distinctive jerk signatures even when their acceleration patterns look similar
- Elevator movements have smooth, low jerk values as they move at constant acceleration
- Stair climbing creates irregular, higher jerk values due to the step-by-step movement pattern
- Running produces high, rhythmic jerk values corresponding to step impacts
- The loose pocket placement amplifies these jerk differences, as the phone moves more freely during high-impact activities, but does not negatively impact values

Implementation impact: Looking at the time series plot, jerk clearly separates:

- High jerk peaks during running

- Moderate but irregular jerk during stair activities
- Low, smooth jerk during elevator movements and stationary periods

This feature specifically addresses the confusion between stair activities and walking-flat seen in the original model, as it captures the abrupt changes in movement that occur when transitioning between steps.

2. Signal Energy Ratio

Physical basis: Different activities distribute energy differently across the frequency spectrum. Rather than looking at absolute energy in specific bands, this feature examines the relationship between high and low frequencies.

Why it's effective for activity recognition:

- The ratio between high and low frequency components is more robust to variations in movement intensity
- Running has significant high-frequency components, giving it a high ratio
- Stair activities have a distinctive mix of frequencies due to their complex movement pattern
- Walking on flat surfaces has moderate frequency content with a balanced ratio
- Stationary and elevator activities have minimal high-frequency content, resulting in low ratios

Implementation impact: The time series plot shows:

- High, consistent ratios during running
- Medium ratios with irregular patterns during stair activities
- Lower ratios during flat walking and elevator movements
- Very low ratios during stationary periods

This feature normalizes the frequency distribution, making it less sensitive to individual differences in movement intensity while preserving the characteristic frequency signature of each activity.

These features specifically target the weakness in the original model - the confusion between stair activities and flat walking - by capturing characteristics that remain distinctive even with a loose pocket placement.

A4 – Indoor Localisation

1: Signal strengths

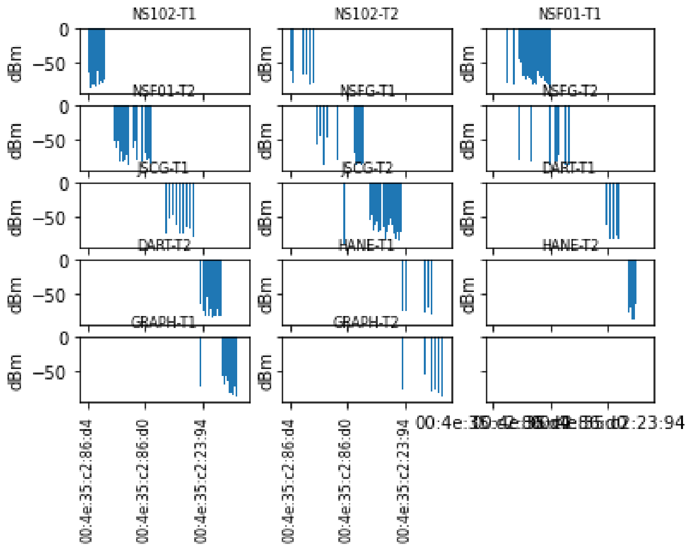


Figure 2: Signal Data

Comments:

Building floor impacts signal strength

1- Ground floor locations (NSFG-T1/T2) show stronger signals averaging about -30 to -40 dBm as opposed to
2- Second floor locations (DART, HANE, GRAPH) consistently show weaker signals, mostly ranging from -50 to -80 dBm

Room position variations

1- NS102-T1 vs NS102-T2: moving across the room causes a decrease in signal strength from the strongest access point
2- In DART, T1 position receives weaker signals from the central access point, whereas T2 recognises stronger strengths based off the saturation in plots (denser groupings of signals identified)

As you shift through rooms, the rooms are connecting to different WIFI's, showing an equal distribution between changing rooms and Wi-Fi strengths

Access point visibility by location

1- Open areas (NSF01-T1) can detect larger number of signals than closed off signals (HANE) indicating weaker signals when separated from router or by a physical phenomenon (walls)

2/3: Similarity Matrix

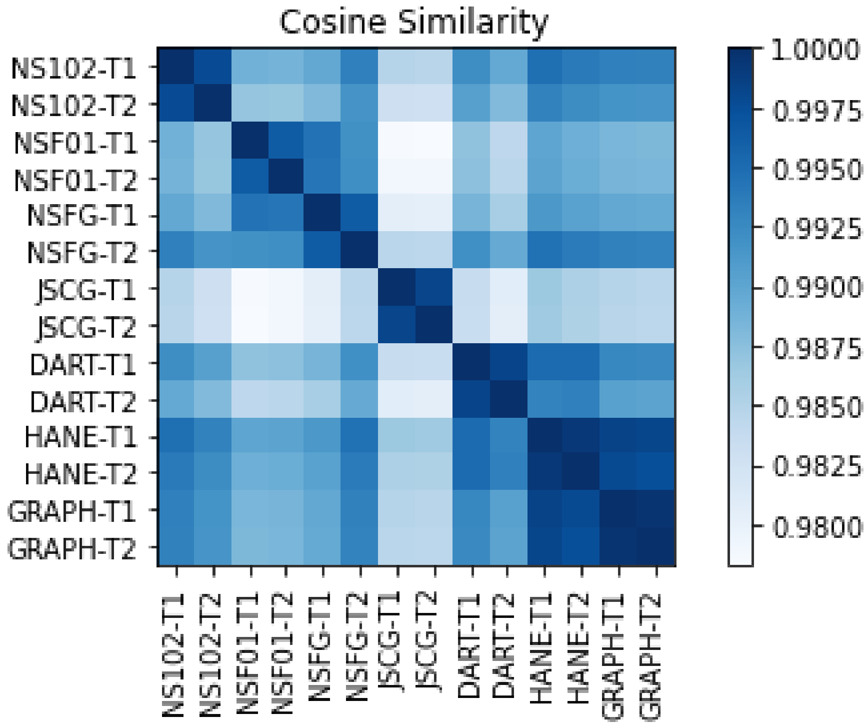


Figure 3: Similarity Data Self

Comments:

- Locations within the same buildings show similarity – NEWSCI building locations (NS102, NSF01, NSFG) form a clear cluster, high similarity between foyer areas
- Second floor localisation (DART, HANE, GRAPH) form a clear cluster, Wi-Fi localisation can differentiate between floors within a building

4: Similarity Matrix (combined)

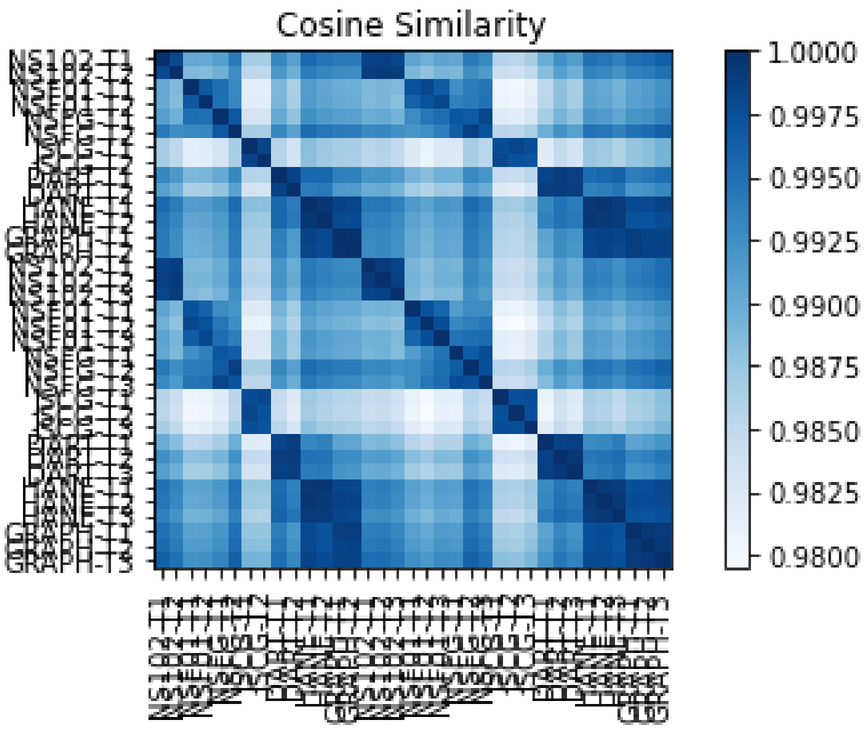


Figure 4: Similarity Data Combined

<u>Comments:</u>

- While individual measurements show high consistency, subtle variations are introduced by the different devices and positioning, strengthening the overall system by capturing a more holistic range of signal variations for each location
- The gradient between floors (NSF01/NSFG to second floor locations) become more defined in the combined data, enhancing the system’s ability to identify vertical positioning
- Combined data is effective as it aggregates multiple signal perspectives, creating more robust location fingerprint. This works because the environmental constants (access point locations, building structures) dominate signal patterns more than variables introduced by different users, location signatures remain distinguishable.