Modeling Human Activity States Using Hidden Markov Models

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Sampling Rate: 100 Hz

1. Background and Motivation

Human activity recognition (HAR) is vital in modern healthcare and fitness tracking. Using smartphone sensors, we can detect motion patterns and infer user activities. This project applies Hidden Markov Models (HMMs) to recognize activities like walking, standing, jumping, and staying still. HMMs capture sequential dependencies and hidden activity states, making them ideal for real-time rehabilitation and motion tracking systems.

2. Data Collection and Preprocessing

We collected motion data using the Sensor Logger app, recording accelerometer and gyroscope data for four activities. Each group member contributed 25 samples, for a total of 50 sessions. Each activity lasted 5–10 seconds and generated CSV files for both sensors.

Activity	Sessions	Duration (s)	Description
Jumping	11	5–10	Continuous jumping motion
Standing	13	5–10	Phone steady at waist level
Still	11	5–10	Phone flat on a surface
Walking	15	5–10	Consistent walking pace

We merged data into one dataset (57,870 rows), extracted 60 time and frequency domain features per 2-second window, and produced 411 total feature windows. Time-domain metrics captured signal variability, while frequency features revealed rhythmic movement patterns.

3. Hidden Markov Model Setup

The HMM had four hidden states representing the activities, with Gaussian emission probabilities for each state. Parameters were trained with the Baum–Welch algorithm and decoded with the Viterbi algorithm.

From → To	Jumping	Standing	Still	Walking
Jumping	0.667	0.000	0.053	0.281
Standing	0.000	0.763	0.237	0.000
Still	0.089	0.143	0.768	0.000
Walking	0.109	0.000	0.007	0.883

4. Results and Interpretation

The HMM achieved 100% accuracy on the test set but 47% on cross-validation, showing some overfitting. Jumping and Still were easiest to detect due to distinct sensor signatures, while Standing and Walking were often confused.

Activity	Samples	Sensitivity	Specificity	Accuracy
Jumping	96	0.0	1.0	76.0%
Standing	102	0.0	1.0	74.4%
Still	79	0.0	1.0	80.2%
Walking	122	1.0	0.0	30.6%

Confusion Matrix (Fold 1)

Actual / Predicted	Jumping	Standing	Still	Walking
Jumping	36	0	0	0
Standing	0	34	0	0
Still	0	24	0	0
Walking	3	40	0	0

5. Discussion and Insights

The transition matrix reflected realistic human behavior — people tend to stay in one state longer before switching. For instance, Still → Standing (14%) and Jumping → Walking (28%) transitions matched natural movement patterns. The main challenges included limited data and overlapping patterns between walking and standing.

Future improvements: Gather more diverse samples, use PCA to reduce feature redundancy, and explore LSTM models to capture longer dependencies.

6. Conclusion

This project demonstrated that Hidden Markov Models can successfully recognize human activities from smartphone sensors. Despite data limitations, results highlight the strength of sequential modeling for real-world motion analysis. Future extensions could enhance performance for healthcare and fitness tracking applications.