POPAyI: Muscling Ordinal Patterns for low-complex and usability-aware transportation mode detection

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Introduction

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- Most TMD literature relies on hand-crafted features (reaching hundreds of features) or computationally- and data-intensive DL methods, which pose challenges for resource-constrained Internet of Things (IoT) scenarios
- We present POPAyI, an innovative strategy based on Ordinal Pattern (OP) transformation applied to mobility-related time series that is computationally efficient, scalable, and provides accurate transportation mode detection.

Ordinal Patterns

A symbolic representation of time series dynamics, capturing intrinsic features without relying on predefined models or heavy computational resources. It needs two parameters:

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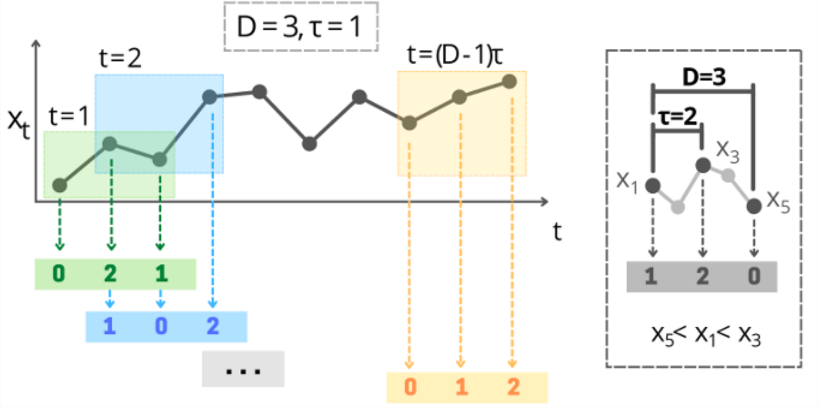
- Embedding delay $\tau \in \mathbb{N}$ to define the interval between consecutive data points

Ordinal Patterns

A lightweight solution well-suited for edge computing applications, enabling on-device analytics while preserving privacy

Ordinal Patterns



Ordinal Patterns Limitations

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2. Originally defined for univariate time series
    - Previous studies have attempted to extend OP to multivariate data, but faced limitations such as increased computational complexity or loss of interpretability

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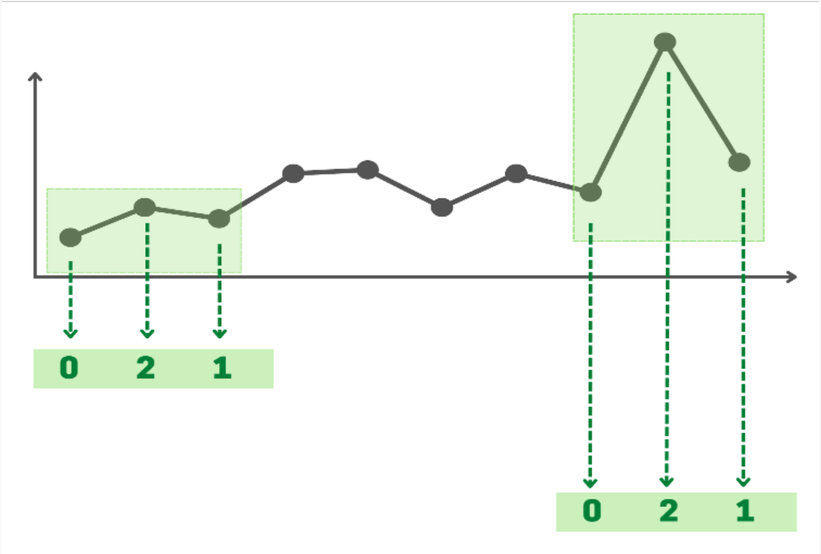

Our approach: PoPayI

POPAyI (Polar Ordinal Patterns with Amplitude Information) is the first work to leverage amplitude information in a multivariate OP approach.

How POPAyI works?

1. Converts 2D spatial data into symbolic patterns based on ordinal relationships between points

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How POPAyI works?

1. Converts 2D spatial data into symbolic patterns based on ordinal relationships between points
2. Uses polar coordinates to handle 2D mobility data (latitude and longitude)
3. Introduces amplitude information to distinguish variations in movement magnitude (e.g., slow vs. fast-moving vehicles)

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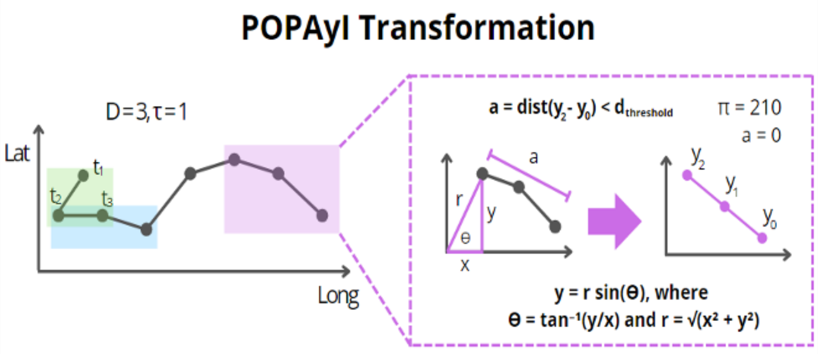

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- Data Handling: Removal of low-quality data, such as out-of-range GPS points and trajectories with fewer than 10 points.

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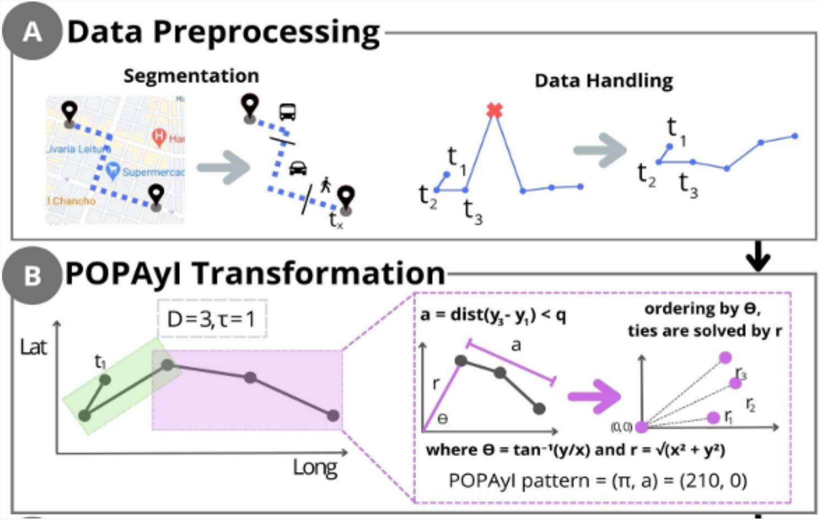
- Polar Coordinates: Patterns are based on the angle and distance of 2D points, capturing non-linear movement dynamics.
- Amplitude Information: Calculates the displacement (distance) between the first and last points in the window, allowing for better distinction between movement types (e.g., slow vs. fast)

Methodology



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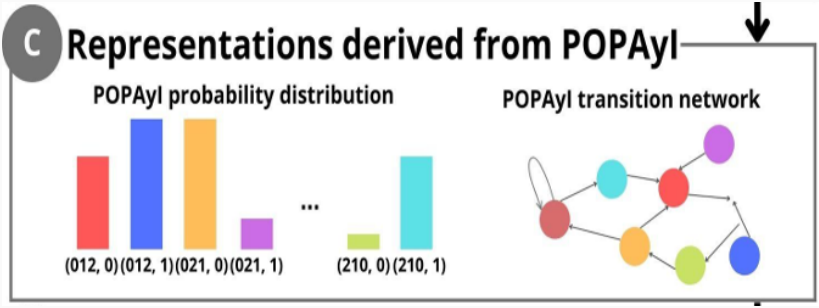
- Transition Network: A graph representation where nodes represent ordinal patterns, and edges represent transitions between patterns
  - Extract features such as Probability of Self-Transition (how likely a pattern repeats itself), Number of Nodes and Edges, and Average Edge Weights, indicating how dynamic or stable the movement is

Methodology



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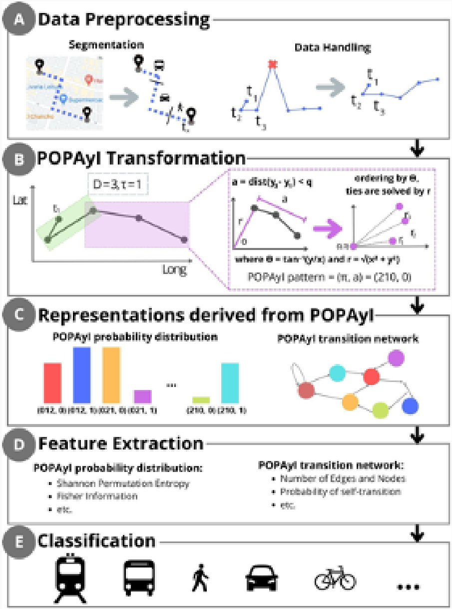
E) Classification:

- Features are fed into an XGBoost classifier

Methodology



POPAyI advantages to TMD i

- Lightweight Approach
  - Time complexity is O(n) due to small and constant embedding dimension (D)
  - Ideal for resource-limited environments, such as IoT
- Scalability
  - Computational efficiency with linear time complexity
  - Works well with large time series and requires minimal space
- Resilience to Trajectory Size
  - Handles trajectories of varying sizes (differently from Deep Learning methods)
  - Adapts to real-world mobility patterns, regardless of trajectory length
- Robustness

POPAyI advantages to TMD ii

  - Resilient to GPS errors and dynamic noise
  - Ensures reliable detection in noisy environments.
- Enhanced Representation
  - Captures 2D temporal dynamics and incorporates amplitude.
  - Improves accuracy in distinguishing transportation modes.

Experiments

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Goal: Evaluate how incorporating amplitude improves detection of vehicle speed variations

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- Compare results with and without amplitude.

Experiments

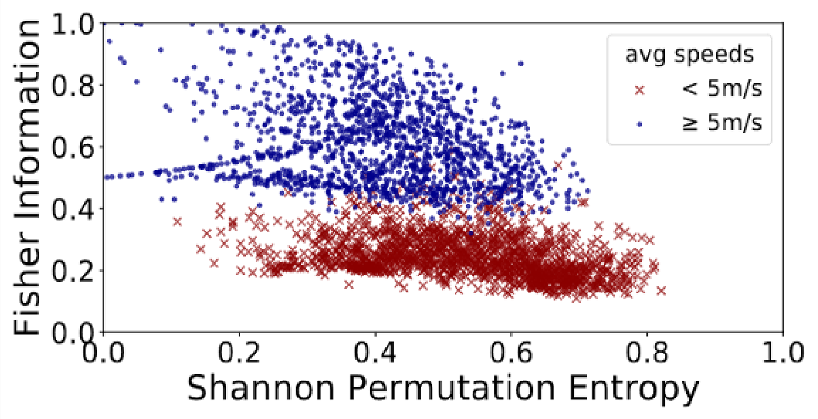

Figure 1: With amplitude: Better separation of vehicle behaviors (clear clusters)

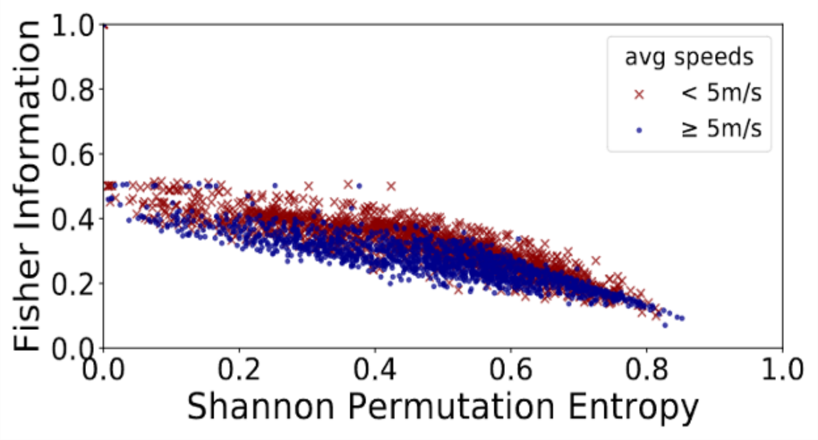

Figure 2: Without amplitude: Poor distinction between slow and fast vehicles

Conclusion: Amplitude information enhances the ability to capture mobility dynamics, improving detection accuracy.

Experiments

Transportation Mode Detection

Goals:

- Predict the transportation mode based on spatiotemporal trajectory data.
- Evaluate the effectiveness of POPAyI in classifying different transportation modes.
- Compare POPAyI to state-of-the-art Machine Learning (ML) and Deep Learning (DL) methods.

Experiments

Transportation Mode Detection

Setup:

- We used GeoLife dataset, which contains 182 users' GPS trajectories over 5 years and various transportation modes: walking, biking, car, bus, subway, train.
- Fixed-length segments of 500 points to ensure comparability across all models
- Classification using cross-validation with 5 folds and stratified classes

Hyperparameters selection

- Explored values:
  - Embedding Dimension: D = 3, 4, 5
  - Embedding Delay: $\;= 1, 2$
  - Amplitude Threshold: q = 0.0005 to 3 (0.5 m to 3 km)
- Selection Process:
  - Used Successive Halving: progressively eliminated weaker configurations based on F1-score
  - $\tau = 2$ consistently achieving the best results suggests that non-consecutive points capture more meaningful transport dynamics
  - Difficulty of establishing a straightforward correlation between hyperparameter values

Final choice: D = 3, $\;= 2$, q = 0.0005

Experiments

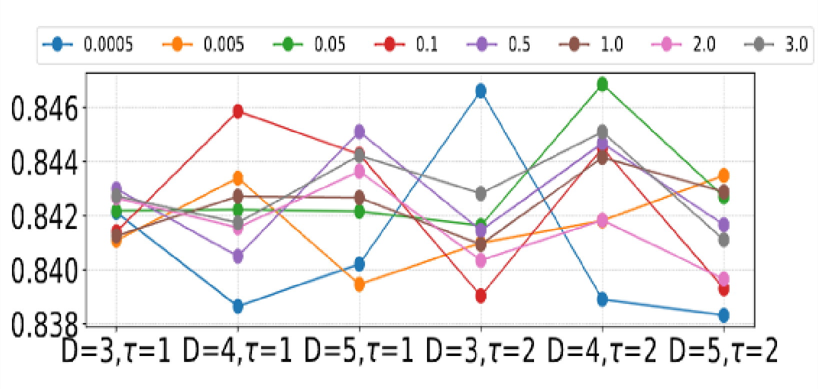

TABLE I: Comparison for different ML methods. $D = 3$, $\tau = 2$, and $q = 0.0005$.

	Accuracy	F1 score	Precision	Recall
SVM	37.36% (± 0.02)	15.62% (± 0.03)	20.35% (± 0.02)	33.82% (± 0.32)
DT	78.96% (± 0.03)	74.67% (± 0.05)	74.77% (± 0.05)	74.65% (± 0.05)
RF	86.35% (± 0.03)	82.53% (± 0.04)	81.64% (± 0.04)	83.72% (± 0.04)
XGBoost	87.12% (± 0.03)	84.02% (± 0.04)	83.28% (± 0.04)	85.90% (± 1.71)

Experiments i

Transportation Mode Detection - POPAyI vs. 1D OP and POP

1D OP:

- Separates feature extraction for latitude and longitude.
- Captures ordinal relationships in 1D space but misses non-linear movement dynamics in 2D mobility data.

POP:

- Polar Ordinal Patterns (POP) use polar coordinates to represent 2D spatial relationships.
- Better suited to capturing complex movement behaviors like turns and changes in direction.

POPAyI:

- Incorporates amplitude information into POP, capturing both direction and magnitude of movement (e.g., speed changes).

Experiments

	D	F1 score	Recall	Precision	No. of Params.
***POPAyI* q = 0.0005**	**3**	84.02% (± 0.04)	83.28% (± 0.04)	85.90% (± 1.71)	7.8×10^1
	4	84.04% (± 0.04)	83.40% (± 0.04)	84.81% (± 0.04)	1.2×10^3
	5	83.49% (± 0.04)	82.80% (± 0.04)	84.32% (± 0.04)	2.8×10^4
POP	**3**	82.24% (± 0.04)	81.23% (± 0.04)	83.47% (± 0.04)	2.1×10^1
	4	82.31% (± 0.03)	81.45% (± 0.04)	83.32% (± 0.04)	3.0×10^2
	5	81.13% (± 0.04)	79.39% (± 0.04)	81.99% (± 0.04)	7.3×10^3
1D OP lat. and long. separately	**3**	78.96% (± 0.05)	78.49% (± 0.05)	78.04% (± 0.05)	2.1×10^1
	4	78.40% (± 0.05)	77.81% (± 0.05)	79.31% (± 0.05)	3.0×10^2
	5	80.81% (± 0.03)	80.16% (± 0.05)	81.63% (± 0.04)	7.3×10^3

Experiments

TABLE III: Quantitative comparison. *POPAyI* with $D = 3$, $\tau = 2$, and $q = 0.0005$.

Transportation modes sets	Methods	Reported F1 score	Reported Accuracy	Reported Recall	Reported Precision	Data size training	No. of feats.	No. of params.
walk, bike car&taxi, bus	DT [1]	74.77%	76.20%	76.37%	76.92%	10-8000	13	-
	POPAyI	86.34% ($\pm$ 0.04)	90.21% ($\pm$ 0.05)	86.56% ($\pm$ 0.0.05)	86.16% ($\pm$ 0.06)	10-8000	19	7.8×10^1
	Light. CNN [2]	87.10% ($\pm$ 1.1)	-	-	-	500	500	1.1×10^4
	POPAyI	86.86% ($\pm$ 0.04)	89.73% ($\pm$ 0.03)	86.74% ($\pm$ 0.04)	87.02% ($\pm$ 0.04)	500	19	7.8×10^1
	POPAyI	87.41% ($\pm$ 0.04)	90.88% ($\pm$ 0.03)	87.41% ($\pm$ 0.05)	87.50% ($\pm$ 0.04)	1000	19	7.8×10^1
walk, bike, car, train bus&taxi, subway	XGBoost [3]	87.40%	90.77%	90.84%	86.46%	10-39120	111	-
	POPAyI	82.40% ($\pm$ 0.07)	86.55% ($\pm$ 0.04)	80.67% ($\pm$ 0.09)	84.57% ($\pm$ 0.07)	10-39120	19	7.8×10^1
walk, bike, car&taxi, bus, train	Best CNN [5]	74.80%	79.80%	-	-	200	200	2.6×10^6
	7 CNNs [5]	83.90%	84.80%	82.42%	86.30%	200	200	1.8×10^7
	LSTM [21]	91.90%	92.70%	91.84%	92.00%	200	200	8.1×10^6
	AE + CNN [6]	88.28%	89.47%	86.99%	89.85%	200	200	4.1×10^7
	Light. CNN [2]	83.90% ($\pm$ 1.10)	-	-	-	500	500	1.1×10^4
	POPAyI	85.68% ($\pm$ 0.03)	87.42% ($\pm$ 0.03)	85.02% ($\pm$ 0.03)	86.50% ($\pm$ 0.03)	500	19	7.8×10^1
	POPAyI	85.77% ($\pm$ 0.03)	89.48% ($\pm$ 0.05)	84.77% ($\pm$ 0.05)	86.99% ($\pm$ 0.04)	1000	19	7.8×10^1
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    - Acceptable mixing of transport types in urban planning.
    - Critical applications require minimal false negatives for safety.
    - POPAyI Advantage: Fewer false negatives between motorized and non-motorized transports enhance safety in critical applications

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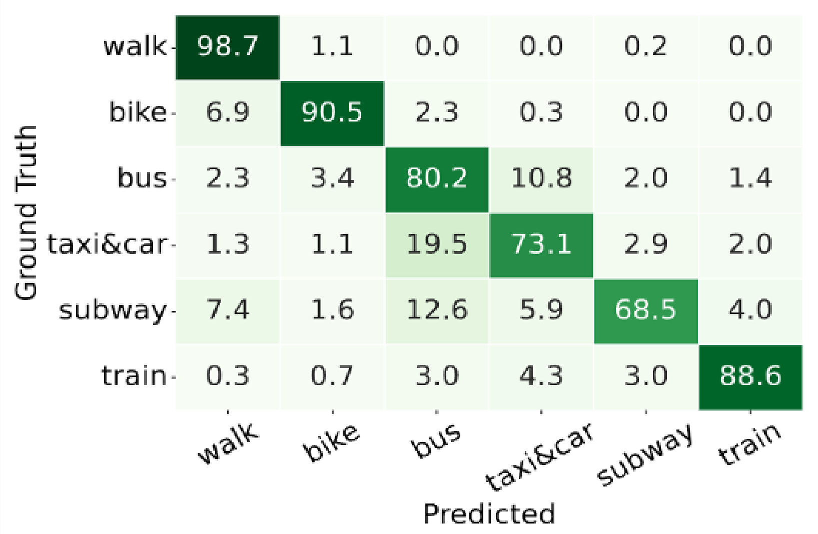

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- Achieves high accuracy with minimal computational resources, making it suitable for resource-constrained environments (e.g., IoT)
- Outperforms traditional methods and DL approaches while maintaining a lightweight framework

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- Incorporate Additional Features: Enhance the model by integrating more features from mobility data, such as environmental factors affecting transport dynamics.