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Gaussian Process Based Motion Pattern Recognition with Sequential Local Models


Mattias Tiger & Fredrik Heintz, Linköping University

Many challenges exist for trajectory analysis on larger road networks with complex structures. Gaussian process based motion patterns have shown great performance for single crossings and we extend the approach to meet these challenges. This includes proposing a novel motion pattern model which goes beyond the traditional flow field approach and incorporates spatial locality together with the discriminatory power of a velocity field. It is shown empirically to out-perform the flow field approach in a setting of sequential local motion pattern models.

Motion Pattern Recognition

Motion pattern recognition is important in vehicular trajectory analysis, maritime traffic classification and for autonomous cars and other robots operating in semi-structured environments.

Include: **clustering, *classification*, prediction, abnormality detection**

Motion pattern modeling:

Given a set of trajectories T_c of class $\boldsymbol{c}$ where each trajectory $\mathrm{T}_{c,k}$ is a time series made up of *data points* $[t \;\; p_x \;\; p_y \;\; v_x \;\; v_y] \in \mathrm{T}_{c,k}$

Represent T_c *with a motion pattern model* $\mathcal{M}_c$

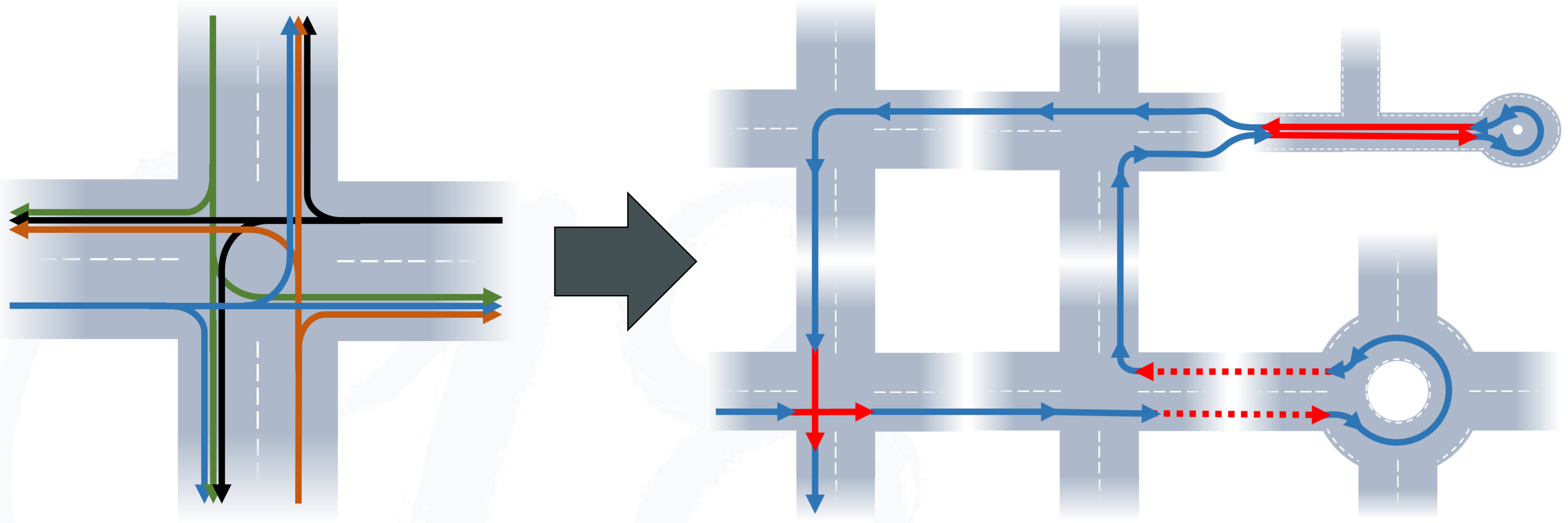
Trajectory classification:

Given a set of motion pattern models $\{\mathcal{M}_c\}_{c=1}^{C}$ and a sub-sequence of a path $\bar{z} = [\bar{p}_x \;\; \bar{p}_y \;\; \bar{v}_x \;\; \bar{v}_y]$

$$\textbf{class} = \underset{\boldsymbol{c}}{\arg\max}\; p(\bar{z} \mid \mathcal{M}_c)\, p(\mathcal{M}_c)$$

Problem Formulation

Moving from a **single crossing** to more **complex road structures.**



Full trajectories from entry to exit can no longer be represented in a unimodal model. Consequently, motion pattern progression of an observed trajectory is no longer trivially computed.

- Self-overlapping trajectories now a problem
- Stops now a problem
- The topology now necessitates sequential local models for trajectory based motion pattern approaches

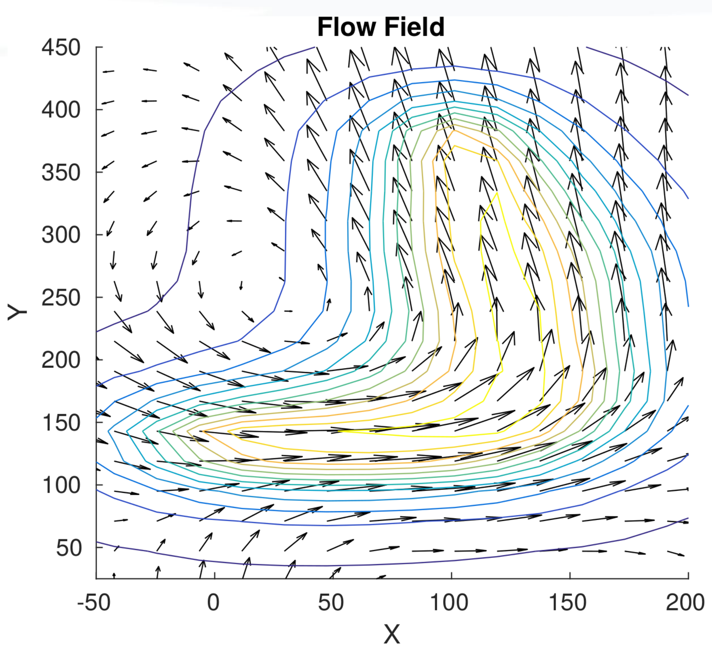
Proposed Model

State-of-the-art **Flow Field** approach

$$(\boldsymbol{p_x}, \boldsymbol{p_y}) \rightarrow \boldsymbol{v_x}, \boldsymbol{v_y}$$

With two GP modelled latent functions:

$$[v_x \;\; v_y] = [f_{v_x}(p_x, p_y) \;\; f_{v_y}(p_x, p_y)]$$



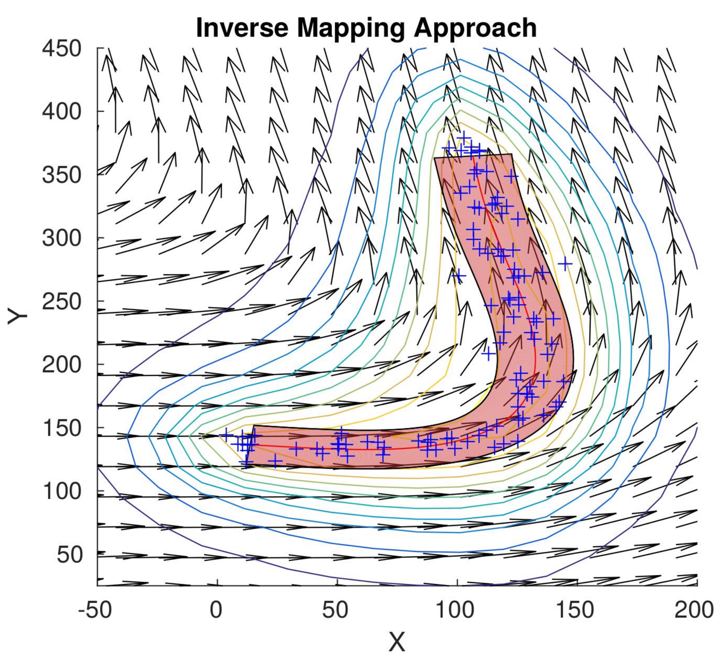
Proposed **Inverse Mapping** approach

$$(\boldsymbol{p_x}, \boldsymbol{p_y}) \rightarrow \boldsymbol{\tau} \rightarrow \boldsymbol{p_x}, \boldsymbol{p_y}, \boldsymbol{v_x}, \boldsymbol{v_y}$$

With five GP modelled latent functions:

$$[p_x \;\; p_y] = [f_{p_x}(\tau) \;\; f_{p_y}(\tau)]$$
$$[v_x \;\; v_y] = [f_{v_x}(\tau) \;\; f_{v_y}(\tau)]$$
$$\tau = f_\tau(p_x, p_y)$$

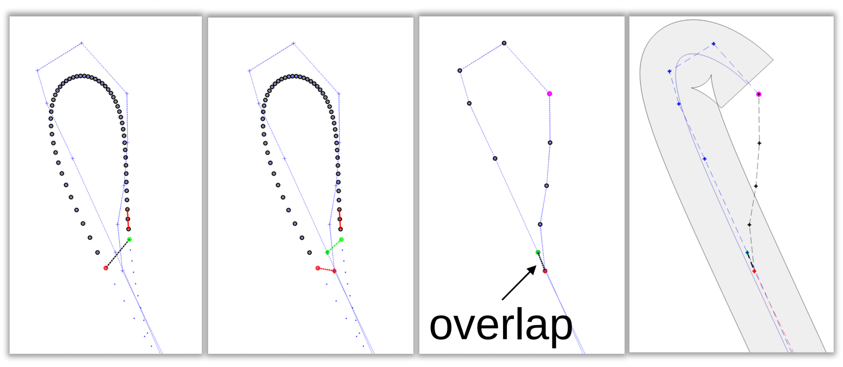
where $\tau \in [0\;1]$ is parametrized time (motion pattern progression)

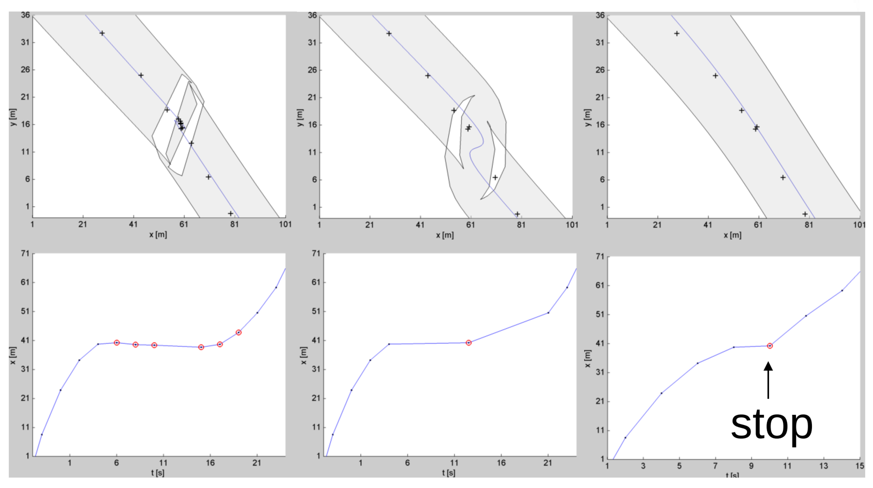


Models *flow*, *spatial extent*, *spatial locality* and *motion progression*.

Proposed Approach

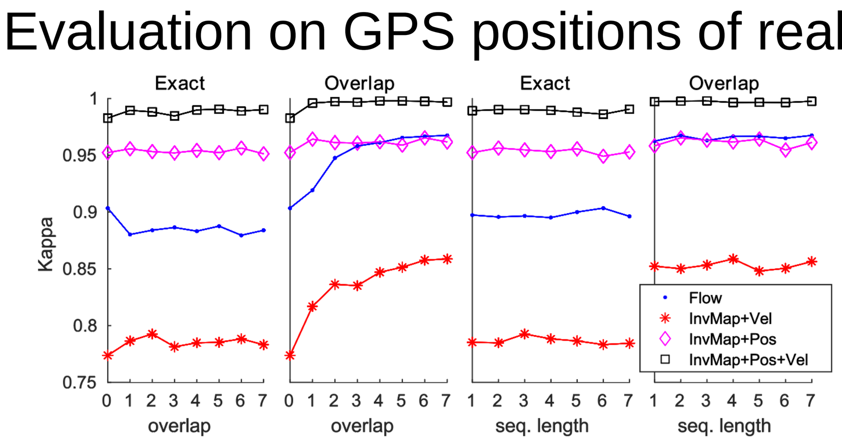
- Approximate τ with μ_τ for $\boldsymbol{\tau} \rightarrow \boldsymbol{p_x}, \boldsymbol{p_y}, \boldsymbol{v_x}, \boldsymbol{v_y}$ mapping
- Stop compression
- Segment at self-overlaps

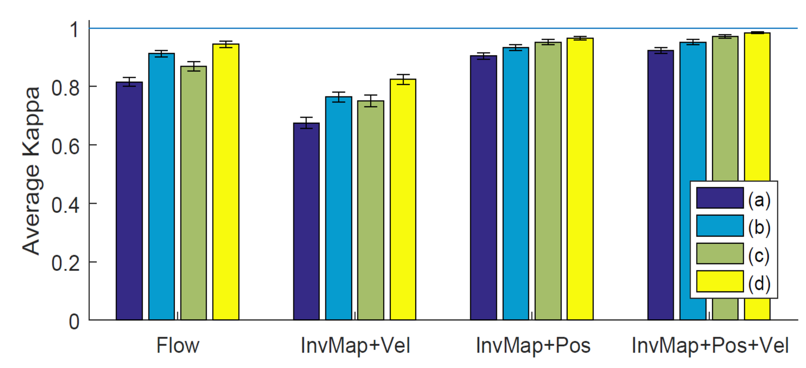




Result

Evaluation on GPS positions of real urban buses (17124 samples).





- Varying the sequential local model overlap significantly affects the velocity field approaches but not so much those using spatial locality.
- Handling self-overlaps and suppressing stops (c),(d) significantly increases the accuracy (Cohen's Kappa).

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