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Predicting Car States through Learned Models of Vehicle Dynamics and User Behaviours


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Motivation

An **Intelligent Vehicular System** would have to infer the intentions of the driver and help or intervene only when needed. For the development of a novel Smart Assistance System we applied a prediction methodology by combining information from both sources – **vehicle and user** – using **Gaussian Processes (GP)** for the prediction of multiple forthcoming low level system states such as position and speed of the car.

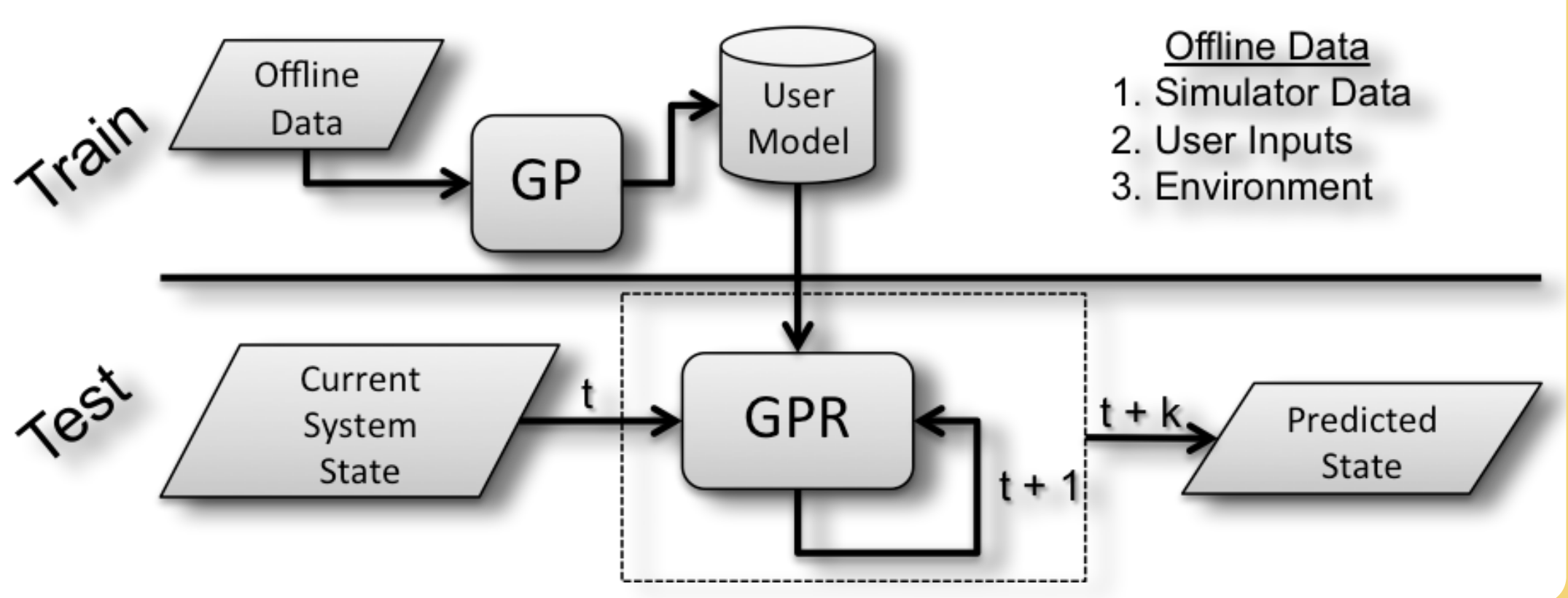
Introduction

We propose a probabilistic approach, using Gaussian Process Regression (GPR)

Implemented a driver's behaviour model

During training, the algorithm builds up a model that describes the user's behaviour combined with the vehicle's dynamics

From which we can infer forthcoming system states

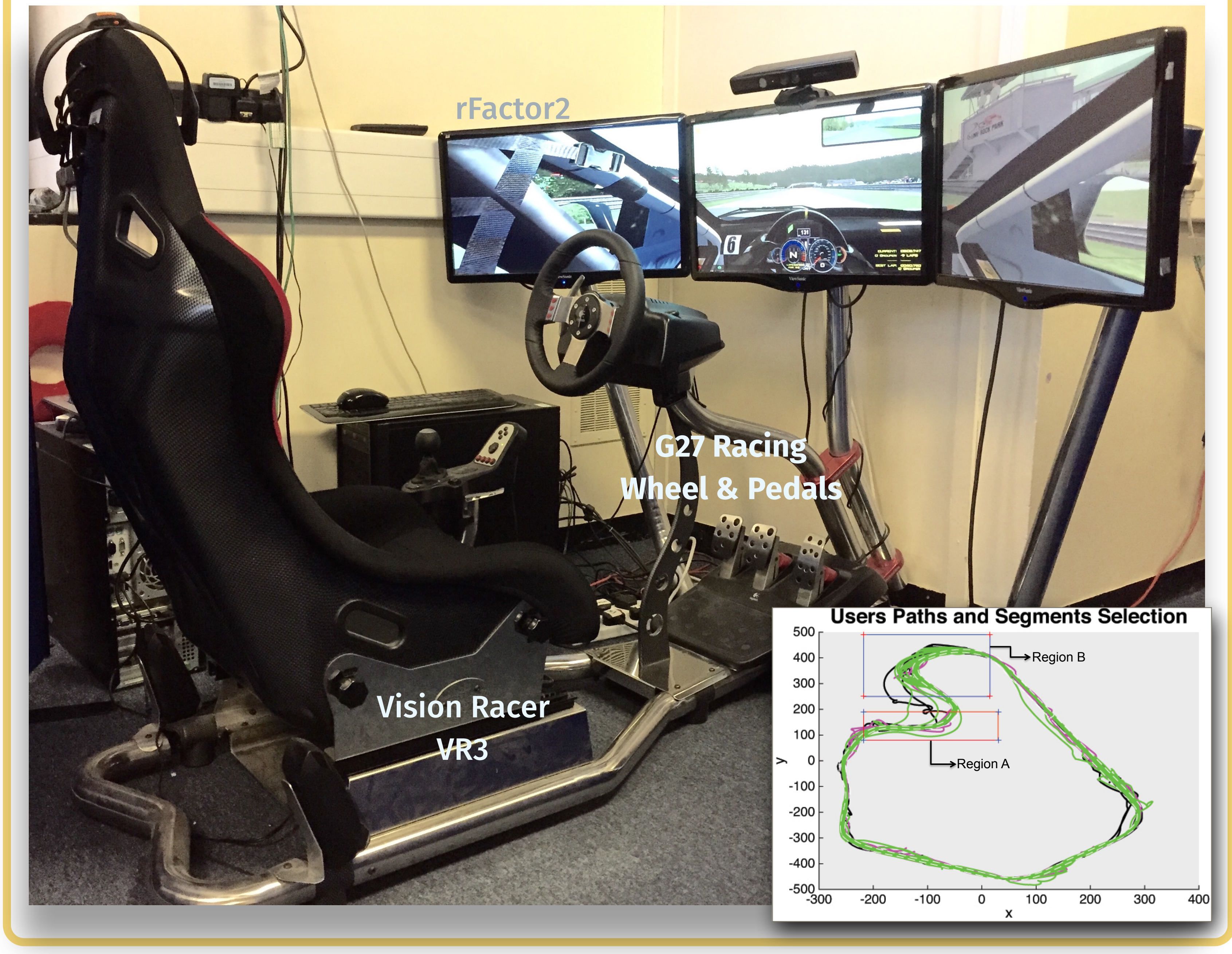


Related Work

- Previous work consists of constructing driver's behaviour models for:
  - Predicting general action patterns (i.e turn left, changing line)
  - Identifying a particular user through a suitable set of inputs
- GPs have been previously used for forecasting time series and modelling dynamic systems with great success.
  - Using **Iterative** or **Direct** approach

The Simulator

The User model is trained by collecting data from the user, vehicle and environment through a racing car simulator at 100HZ.



Model, Selection and Data Analysis

Gaussian Process

Gaussian Process is a collection of random variables, any finite number of which have a joint Gaussian Distribution

1. System

- System Function $y = f(x) + \varepsilon$

Latent Function

Gaussian Distributed Noise

- Prior $p(f|X) = \mathcal{N}(f|0, K)$
- Gram Matrix (Kernel)

Training Data

$$K = k(x_i, x_j), \forall i, j \in \{1, \dots, N\}$$

- K is the sum of two Kernels:
  - Square Exponential

$$k_{SE}(x_n, x_{n'}) = \sigma^2 \exp\left(-\frac{(x_n - x'_n)^2}{2l_n^2}\right)$$

  - Rational Quadratic

Hyperparameters

$$k_{RQ}(x_n, x_{n'}) = \sigma^2 \left(1 + \frac{(x_n - x'_n)^2}{2al_n^2}\right)^{-a}$$

2. Train GP

- Find the Marginal Likelihood (ML)

Hyperparameters

$$p(f|X, \Theta) = \mathcal{N}(y|0, K + \sigma^2\mathbb{I})$$

- Maximise the Log ML

$$\log p(y|X) = -\frac{1}{2}y^T(K + \sigma^2\mathbb{I})^{-1}y - \frac{1}{2}\log|K + \sigma^2\mathbb{I}| - \frac{N}{2}\log(2\pi)$$

3. Make Predictions

- Mean $\mu(x^*) = k(x^*, x)(K + \sigma_n^2\mathbb{I})^{-1}y$
- Variance $\sigma^2(x^*) = k(x^*, x^*) - k(x^*, x)(K + \sigma_n^2\mathbb{I})^{-1}k(x, x^*)$

$$k(x^*, x) = [C(x^*, x^1), \dots, C(x^*, x^N)]$$

Covariance Function K

Model

- AutoRegressive models through 33 GPs
- State on time t predicts the change at t+1 $\tilde{X}_t \rightarrow dx = X_{t+1} - X_t$
- Models of 2 properties:
  - ✦ Steps ahead in time
  - ✦ State with current or/and past inputs

Data Analysis

- Users carried out 2 sessions of 15 laps each
- Several models created

Variables of the User Model in the GPR Algorithm

33 Variables	
1. Brake	9. X/Y/Z Local Acceleration
2. Steering	10. X/Y Local Velocity
3. Throttle	11. X/Y Global Velocity
4. Gear	12. Wheel's Rotation (x4)
5. Pitch	13. Wheel's Lateral Force (x4)
6. Roll	14. Wheel's Suspension Deflection
7. Yaw	15. Wheel's Suspension Force (x4)
8. Speed	16. Engine RPM
	17. Time

Experimental Results

- Multiple 2-second predictions from two segments were analysed
- Models compared according to the average RMSE score of all predictions
- Most results are below the baseline

2 Sets of Results:

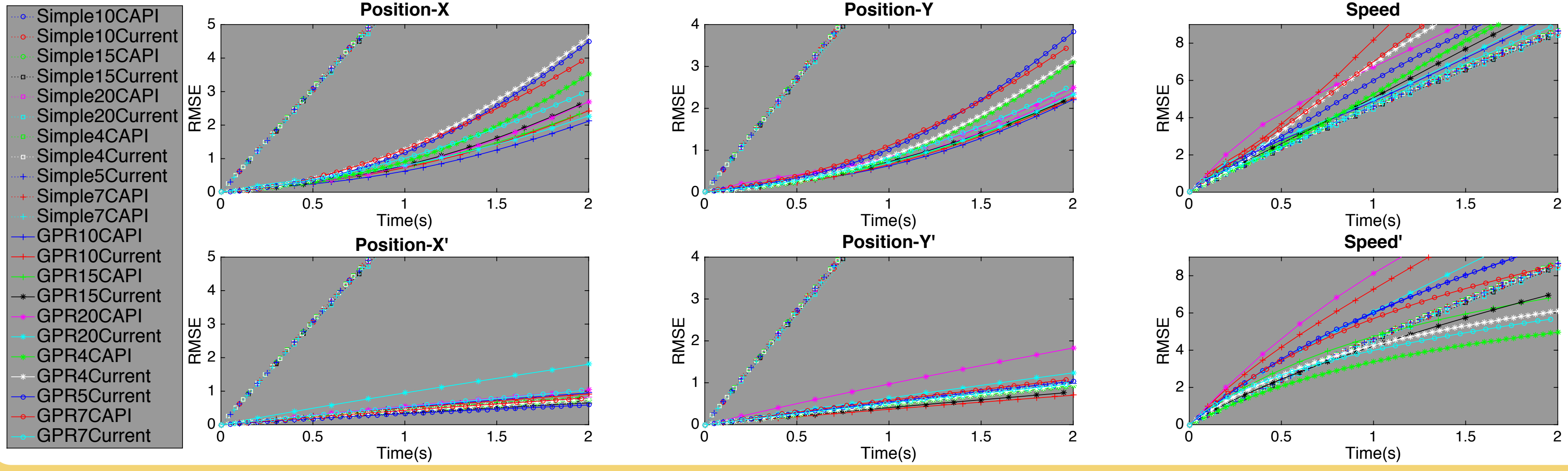
1. 33 Variables are predicted on each step

2. 1 Variable is predicted on each step (denoted by ')

Model Suitability and RMSE values for 1 and 2 seconds predictions for Regions A and B and their improvement.

Variables	Best GP-Models	1s RMSE	2s RMSE
Region A			
Position-X	10 Current/CAPI	0.55	1.75
Position-Y	15 Current/CAPI	0.61	1.92
Speed	20 Current / 25 CAPI	3.04	6.12
Region A'			
Position-X'	10 Current	0.52	1.01
Position-Y'	25 Current	0.64	1.23
Speed'	25 CAPI	2.11	3.47
Region B			
Position-X	10 CAPI	0.63	2.12
Position-Y	10 CAPI	0.63	2.21
Speed	7 Current	4.66	8.87
Region B'			
Position-X'	5 Current	0.33	0.59
Position-Y'	10 Current	0.37	0.70
Speed'	4 CAPI	3.37	4.96

Region B Results



Simple 10 Current

Constant Model (Baseline)

Only Current inputs

Steps ahead

GPR 15 CAPI

Gaussian Process Model

Current and previous inputs

Conclusion

- Results after 1 and 2-second projections over different users maintain low RMS error for 2D position and speed of the vehicle
- The predictions are entirely from a probabilistic approach trained through created states of a particular user
- There was no prior knowledge of any kinematic formulae by the model
- A variance is also predicted and uncertainty is known