Objective-Based Control for Intelligent Vehicles Under Uncertainty

James Fleming

Loughborough University, UK

With thanks to my collaborators and colleagues:
Jakub Krol, Bani Anvari, Laura Justham, Mohammad Otoofi, Leo Laine, Roberto Lot, Neville Stanton, Xingda Yan, Leon Henderson, Qianyue Luo, Hui Zhang, Will Midgley

Loughborough University

Institution of MECHANICAL ENGINEERS

MICG-IMechE mini symposium
UKACC CONTROL 2024

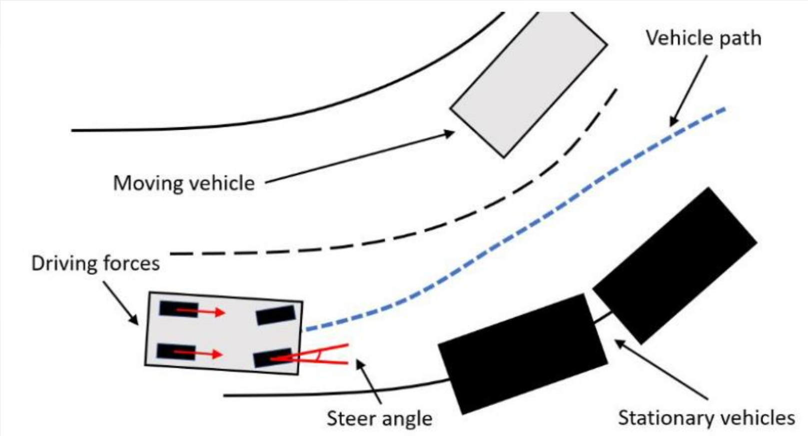
- **Introduction:**
  - **What do I mean by ‘objective-based’ control?**
  - **Why do we care about uncertainty?**

- Some methodologies and case studies:
  - Robust perception and sensing - road surface friction estimation from camera images
  - Control to meet objectives despite uncertainty - robust and stochastic MPC
  - What should the objectives be? – energy efficient ACC systems

- Conclusion:
  - Some closing thoughts and open research questions

What is 'objective-based' control?

- Methods that try to minimise/maximise an objective (cost or reward) function,
- Can account for constraints, e.g. for collision avoidance (explicitly or via objective function)



Examples:

- MPC and its variants (nonlinear, robust, economic…)
- RL algorithms, like DDPG, TD3…
- Control barrier functions resulting in QPs.... etc.

Why?

- In complex situations, easier to specify goals, i.e. 'what we want' than 'how to get it'
- Can include 'economic' objectives, e.g. fuel/energy saving for the vehicle

Motivation - why care about uncertainty?

- Situations with limited visibility common while driving
- Also changing weather conditions, reduced grip from tyres on road

- If possible, should drive 'defensively' in these situations
- How can we make controllers that do this 'automatically'?

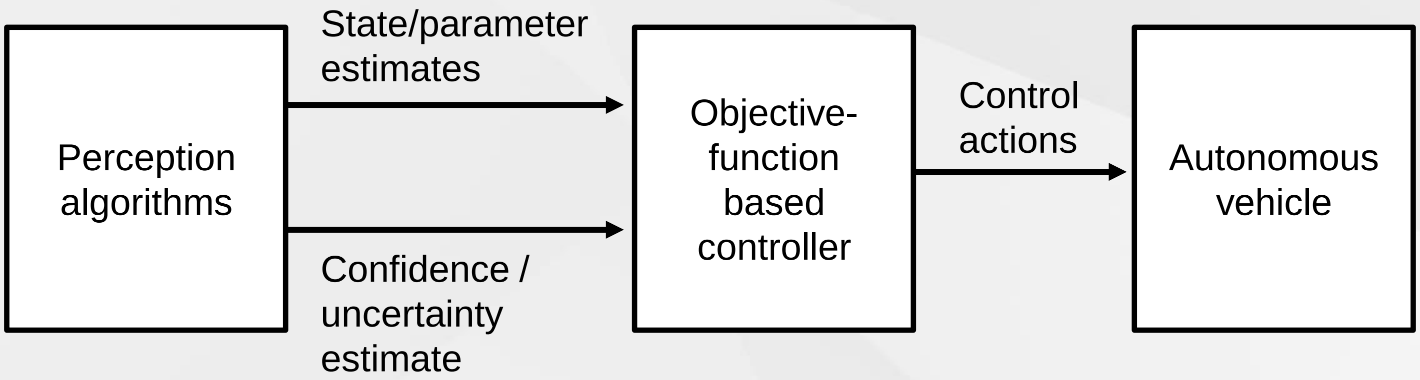
Some thoughts:

- Need to make perception algorithms that are **robust** to reduced visibility
- Design controllers that optimise/meet objectives despite this **uncertainty**
- Ideally, perception algorithms should give some idea of the **confidence** of their detections/measurements

From Google Street View, ©Google, 2024

www.rac.co.uk/drive/advice/winter-driving/understanding-aquaplaning/ , ©RAC, 2024

Framework: objective-based control with uncertainty



Can we do this with current methods?

- Introduction:
  - What do I mean by ‘objective-based’ control?
  - Why do we care about uncertainty?
- Some methodologies and case studies:
  - **Robust perception and sensing - road surface friction estimation from camera images**
  - Control to meet objectives despite uncertainty - robust and stochastic MPC
  - What should the objectives be? – energy efficient ACC systems
- Conclusion:
  - Some closing thoughts and open research questions

Uncertainty in perception

How to make perception methods that are robust to uncertainty, and give uncertainty estimates?

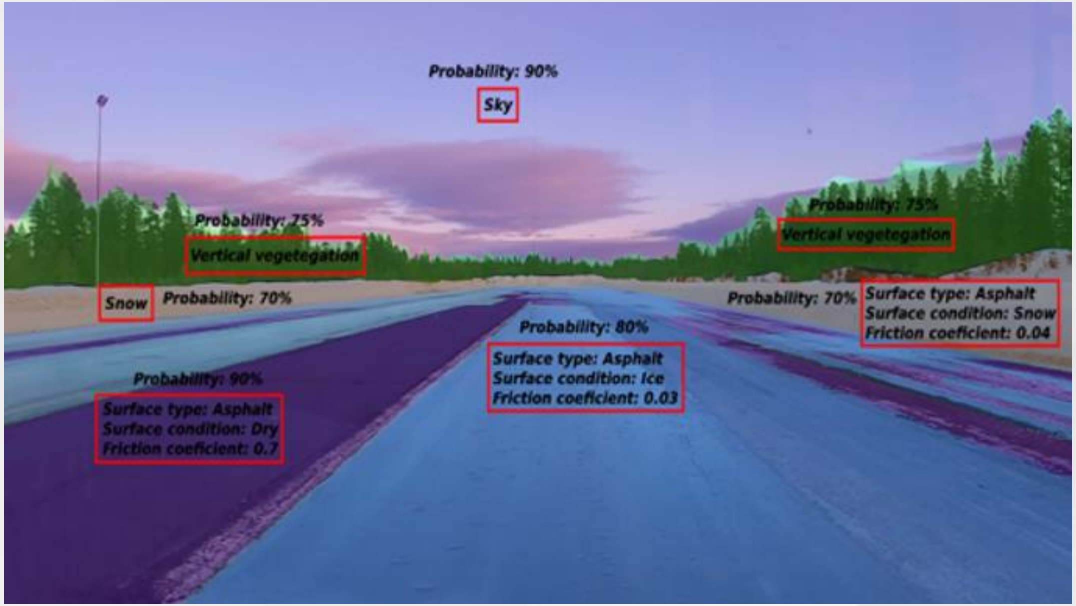
- Classically - (extended) Kalman filter provides an uncertainty estimate via covariance matrix!
- e.g. in mobile robotics EKF-based SLAM can give covariance matrices for position.

However, modern vehicles now have cameras, lidar…

- These give complex, high-dimensional data, typically processed with ML - how to make perception robust and get uncertainty estimates?

Case study: friction estimation

- **Recent collaboration with Volvo Trucks in Sweden**
- **Estimate friction coefficient and surface type/condition**
  - Combined regression and semantic segmentation problem, using a camera on the truck
  - Semantic seg. commonly studied in the ML community, but to date few studies considering e.g. ice, snow, wet asphalt surfaces
  - Would like a method lightweight enough to run in real time ~ 10Hz



Data collection

- GoPro camera
- Data logger
  - RT3000 data collection (acceleration, gyro)
  - Truck CANbus signals

- Three test campaigns, carried out with assistance of Volvo Trucks in Sweden
- Different surface types and conditions
- 1700 vehicle dynamic responses

Testing campaign	Footage length	Surface types	Surface conditions	Num of synced frames	Num of friction samples
Winter test 2021	47 mins	Ice	-	76000	2700
		Snow			
Winter test 2022	3h 20 mins	Ice	-	335000	45000
		Snow			
Spring test 2022	10 h 30 mins	Asphalt	Dry	770000	11000
			Wet		
		Unpaved	Dry		
			Wet	-	-

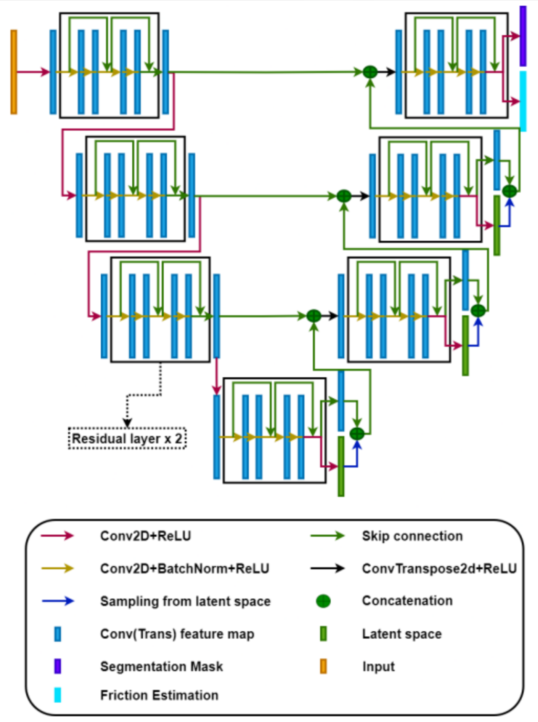
Some examples of road scenes in dataset

Deep learning Model for friction estimation

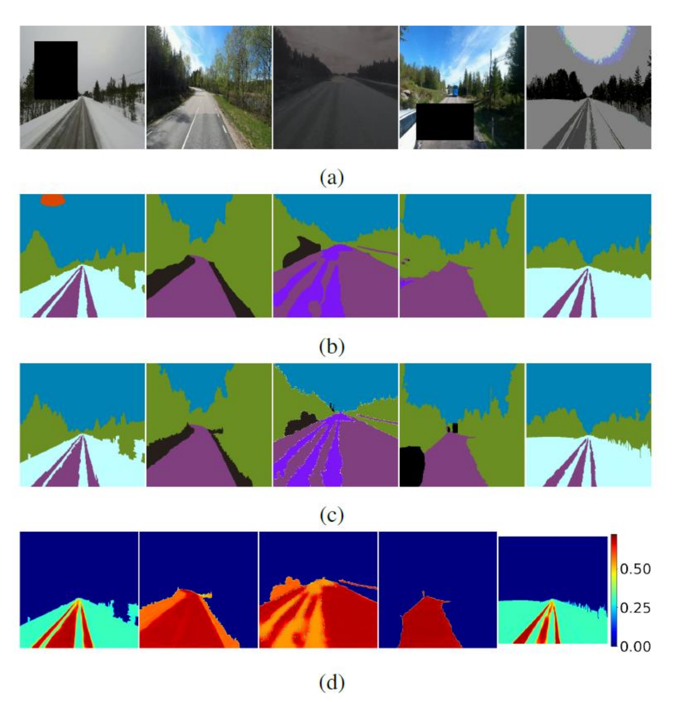
- Conditional Variational Autoencoder (CVAE)
  - ‘U-net’ encoder-decoder architecture, now popular in medical image segmentation, a generative model
  - Learns low-dimensionality ‘latent spaces’ on which the data is approximately normally distributed **– improve robustness**

- Friction estimation also from the CVAE
  - Model trained to perform regression and classification of image pixels simultaneously
  - Semantic understanding of surface type and condition (hopefully) benefits friction estimation

$$\mathcal{L}_{\lambda HVAE} = \frac{1}{L}\sum_{1}^{L} \mathbb{E}_{q_{z_{<i}\sim q_\phi(z|x,y)}}[KL(q_i(z_i|z_{<i},x,y)||p_i(z_i|x,z_{<i}))] - \lambda_s \mathbb{E}_{z\sim q_\phi(z|x,y)}\left[\log p_\theta(y_s|x,z)\right] - \lambda_f \mathbb{E}_{z\sim q_\phi(z|x,y)}\left[\log p_\theta(y_f|x,z)\right]$$



Semantic segmentation: results



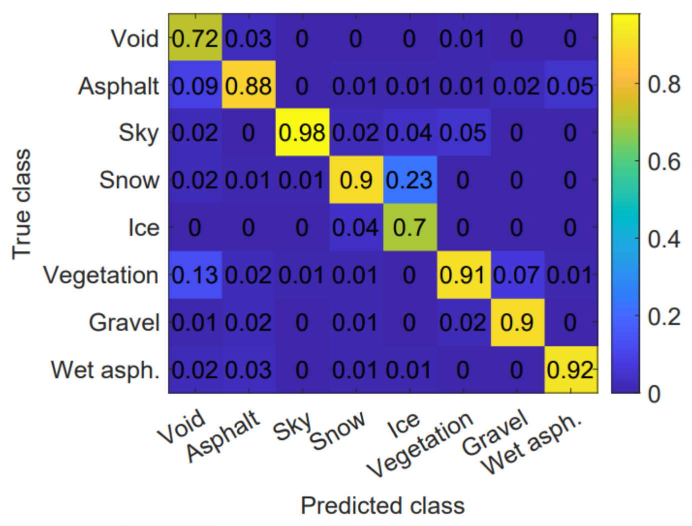


Fig. 5: (a): Input images, (b): Predicted segmentation masks, (c): Ground truth, (d): Predicted friction masks

Friction estimation: results

Also tested the friction estimation performance using several ABS assisted stops on a test track in Sweden:

TABLE I: Performance evaluation of FrictionSegNet_V: 5 braking instances per class.

Surface subjected to testing	Achievable ABS friction*	Estimated friction*	RMSE
Gravel	0.49, 0.55, 0.51, 0.57, 0.44	0.56, 0.54, 0.55, 0.55, 0.58	0.07
Asphalt	0.71, 0.76, 0.75, 0.8, 0.83	0.69, 0.7, 0.72, 0.7, 0.75	0.06
Snow	0.27, 0.39, 0.48, 0.32, 0.28	0.28, 0.31, 0.3, 0.3, 0.29	0.09
Ice	0.16, 0.19, 0.14, 0.15, 0.12	0.12, 0.13, 0.11, 0.1, 0.1	0.04
Wet asphalt	0.53, 0.55, 0.59, 0.67, 0.41	0.57, 0.49, 0.51, 0.58, 0.5	0.07

- Performance for classification of surface type and friction estimation seems good

- Snow is sometimes (~20%) misclassified as ice, but also hard to distinguish for humans.

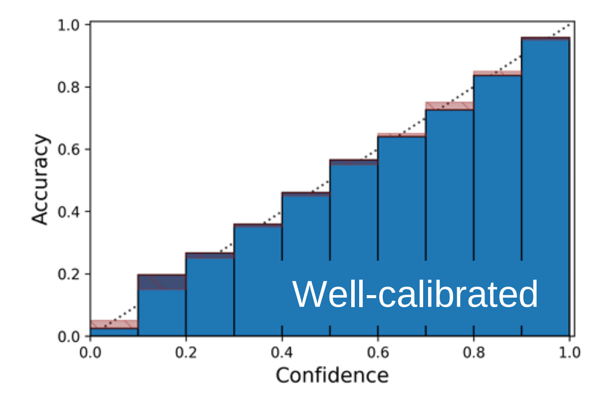
Perception: how to get uncertainty estimates?

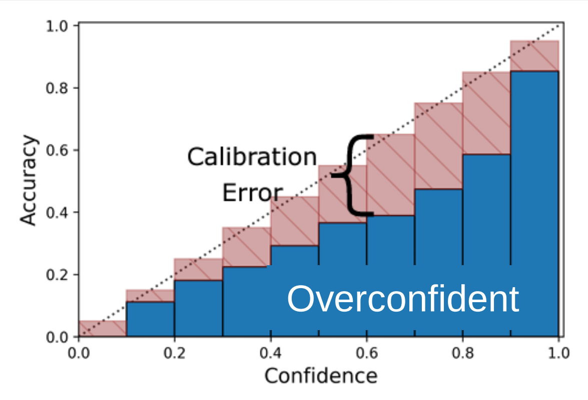
- In principle, final 'softmax' layer gives a probability distribution – actually $p(y|x)$, the conditional distribution of the output given the data – i.e. quantifies the uncertainty

- i.e. a vector like:

$$[p_{snow}\ p_{ice}\ p_{asphalt}\ \ \cdots]$$

- How do we know this probability reported by the network is correct?





- Much of the ML literature focuses on improving accuracy, not calibration...

- For surface type and condition task, we are investigating how to improve calibration (currently overconfident)

- Introduction:
  - What do I mean by ‘objective-based’ control?
  - Why do we care about uncertainty?

- Some methodologies and case studies:
  - Robust perception and sensing - road surface friction estimation from camera images
  - **Control to meet objectives despite uncertainty - robust and stochastic MPC**
  - What should the objectives be? – energy efficient ACC systems

- Conclusion:
  - Some closing thoughts and open research questions

What control methods can account for uncertainty?

- If we have uncertainty estimates, what (objective-function based) control methods can use them?

- Nowadays, lots of robust and stochastic MPC methods are known!
  - Stochastic methods can exploit knowledge of distribution of uncertainty

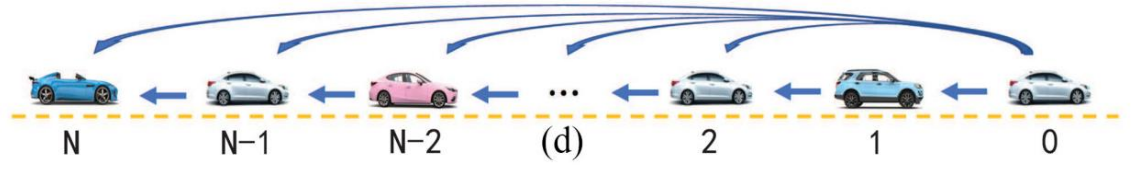
- Why MPC? Can use model to predict effect of uncertain parameters, additive disturbances, etc – many types of system & uncertainty considered in literature

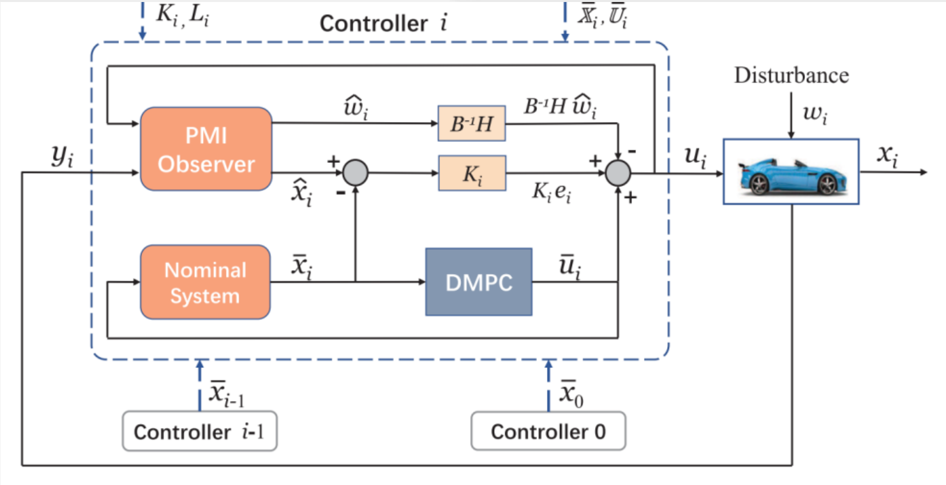
- The above is also true for model-based RL, but no stability/performance guarantees

- This isn't a talk about MPC, so no gory details here, instead an example…

Example: Robust MPC for vehicle platoon control

- Collaboration with researchers at Beihang University
- Acceleration and braking control of a vehicle platoon, with communication from leader and to followers
- State constraints to avoid collisions between vehicles, each vehicle controlled by a tube MPC robust to additive disturbances
- Also considered using an observer to estimate the disturbance



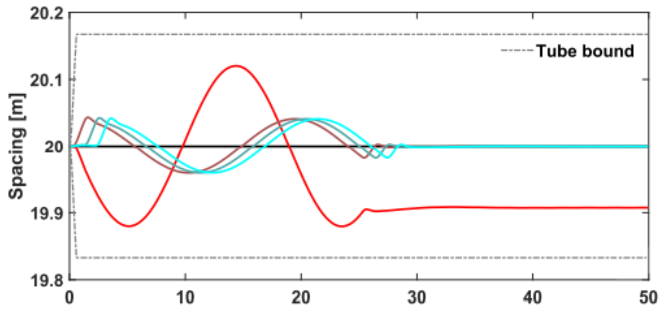


Example: Robust MPC for vehicle platoon control

- Simulation results showed that estimating the disturbance could improve performance

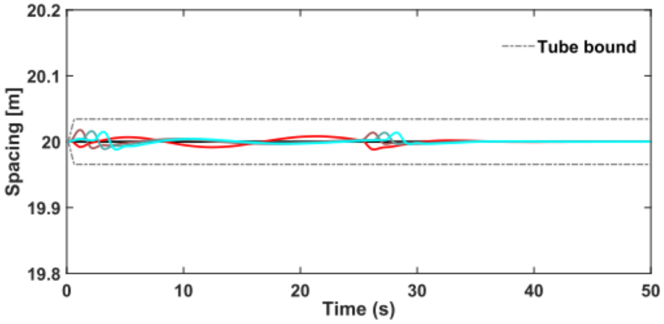
- Some nice theoretical properties: recursive feasibility, stability, assuming the disturbance is bounded

Robust MPC:



(b)

With observer for disturbance:



*Luo, Q., Nguyen, A.T., Fleming, J. and Zhang, H., 2021. Unknown input observer-based approach for distributed tube-based model predictive control of heterogeneous vehicle platoons. IEEE Transactions on Vehicular Technology, 70(4), pp.2930-2944.

Current EPSRC grant at LU

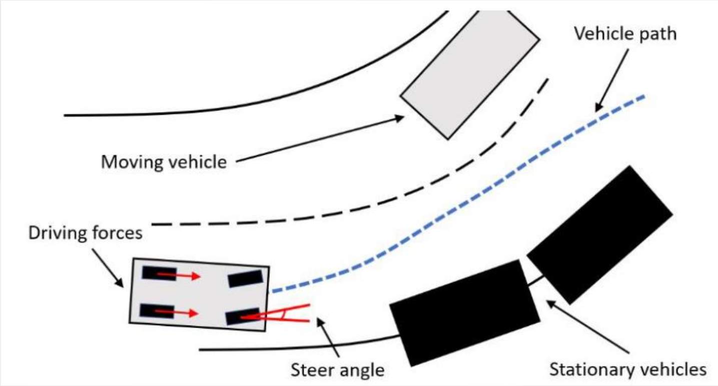
"Learning of safety critical model predictive controllers for autonomous systems" (EP/X015459/1)

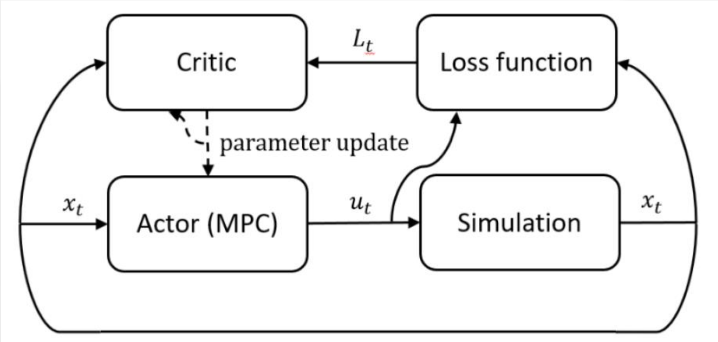
Two current 'objective-based' approaches:

- *MPC (safety guarantees, but complex to design and implement, must redesign for every vehicle)*
- *Reinforcement learning – ('design' is easy as it is automated, but no stability/feasibility guarantees)*

Idea: Can we 'reinforcement learn' an MPC controller in an actor-critic framework?

Could give us the best of both worlds, i.e. a safe controller that is learned automatically from data.





- Introduction:
  - What do I mean by ‘objective-based’ control?
  - Why do we care about uncertainty?
- Some methodologies and case studies:
  - Robust perception and sensing - road surface friction estimation from camera images
  - Control to meet objectives despite uncertainty - robust and stochastic MPC
  - **What should the objectives be? – energy efficient ACC systems**
- Conclusion:
  - Some closing thoughts and open research questions

What objectives would we like to optimise?

We can distinguish between:

- **Near-term**, measurable control objectives, expressible as an objective function, that you might include e.g. in MPC or RL
- Longer-term objectives that are wider **requirements or goals** for the system, but that don't obviously relate to some objective function

Examples:

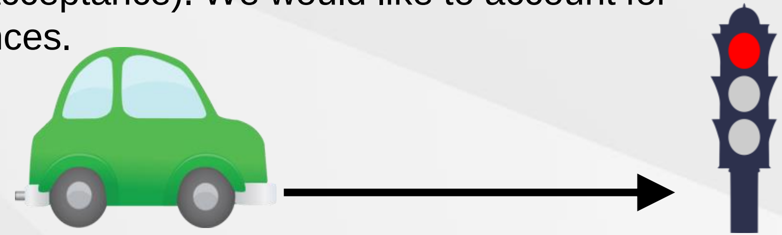
- Safety / collision avoidance
- Minimisation of journey time
- Energy efficiency
- User acceptance
- Have beneficial effects on traffic

What objective functions should we specify for these?

Case study: Energy-saving ACC systems

EPSRC project "Green Adaptive Control for Future Interconnected Vehicles":

- Aimed to develop energy saving optimal control methods for **adaptive cruise control (eco-ACC)** or **autonomous vehicles**, with good user acceptance.
- Just driving more slowly is not an option (poor user acceptance). We would like to account for **preferences** on speed, acceleration, following distances.
- Example: How to **decelerate** before stop signals?



Potential impact:

- Combustion engine vehicles: "The difference in fuel consumption and emissions due to driving behaviour can be **up to 25%** in urban areas" (*UDRIVE project, D45.1*)
- Electric vehicles: Experimental studies on eco-driving assistance have shown **~15% reduction** in energy usage (e.g. Dib et al, 2014, "Optimal energy management for an electric vehicle in eco-driving applications", *Control Engineering Practice*)

Energy-saving ACC as an optimal control problem

- Driving to minimise energy loss is an **optimal control** problem (OCP), can **solve it numerically** to control vehicle
- We add a term to **blend energy-saving behaviour** with **typical human behaviour** – for better user acceptance.
- For **ACC**, it turns out that human car-following behaviour is well-represented by a cost function of the form*:

$$L_d = \delta^2 \left(\frac{v}{v_0} - 1\right)^2 + \left(\frac{u_a}{a}\right)^2 + \left(\frac{u_b}{b}\right)^2 + \beta \frac{(s/s_t - 1)^2}{(s^2/s_t^2 + 1)}$$

*Fleming et al, 2020. "Incorporating driver preferences into eco-driving assistance systems using optimal control". *IEEE Trans. on Intelligent Transportation Systems*.

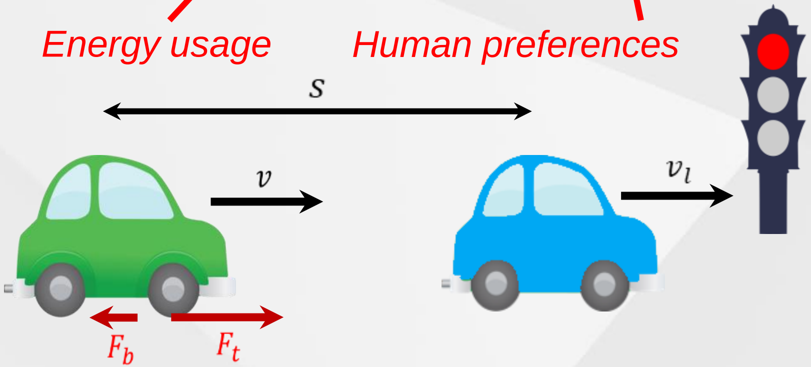
$$\text{minimise} \quad \int_0^T [\alpha L_{loss} + (1-\alpha) L_d]\, dt$$

$$\text{s.t. } m\dot{v} = F_t - F_b - F_{drag}(v)$$

$$\dot{s} = v_l - v, \qquad s \geq 0, \qquad v \leq v_{max}$$

+ initial conditions

Energy usage *Human preferences*



- Can implement in practice using economic / nonlinear MPC
- **Useful**: avoids unnatural behaviour, improves user acceptance compared to minimising energy

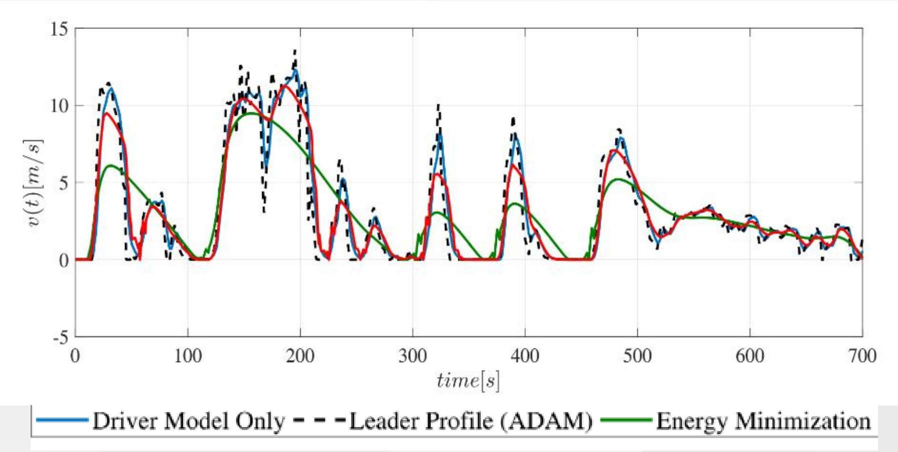
Results: Energy saving ACC

$$\text{minimise} \int_0^T [\alpha L_{loss} + (1-\alpha)L_d]\, dt$$
$$\text{s.t. } m\dot{v} = F_t - F_b - F_{drag}(v)$$
$$\dot{s} = v_l - v, \qquad s \geq 0, \qquad v \leq v_{max}$$
+ initial conditions

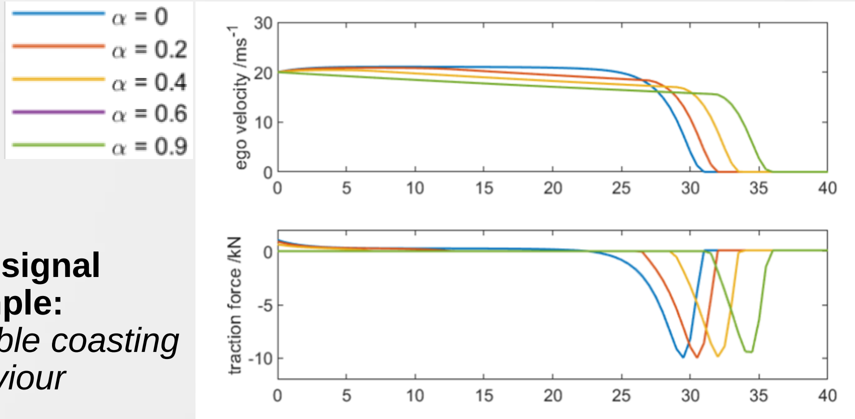
Human preferences

Real-world car-following data example:

(true energy-minimisation behaviour is unnatural!)



Stop signal example:
Variable coasting behaviour



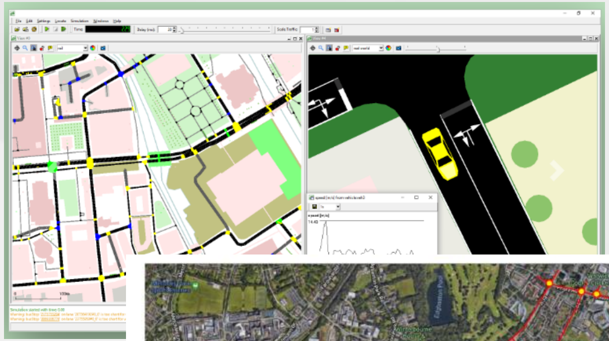
Case study: effect on other traffic?

What is the wider effect of driving like this on other traffic?

Recent results of a collaboration with researchers at UCL using SUMO microscopic traffic simulation:

Eco-vehicle type	Ratio of Eco-vehicles in the network: 5%	10%	15%	25%	50%
	ΔE_n (30) for **conventional vehicles** (IDM based)				
NATURAL	0.0%	0.4%	0.8%	2.2%	0.3%
ECO	1.2%	2.2 %	4.6%	**5.1%**	1.6%
BALANCED	2.7%	3.0%	2.7%	2.3%	3.2%
	ΔE (30) for **eco-vehicles**				
NATURAL	10.1%	10.6%	10.1%	14.1%	14.0%
ECO	17.2%	16.7%	17.3%	22.7%	19.3%
BALANCED	15.1%	14.9%	11.8%	14.5%	**22.7%**

- Also saves energy for other vehicles following ours,
- (e.g. by coasting down before stop signals)
- no/negligible increase in travel times.



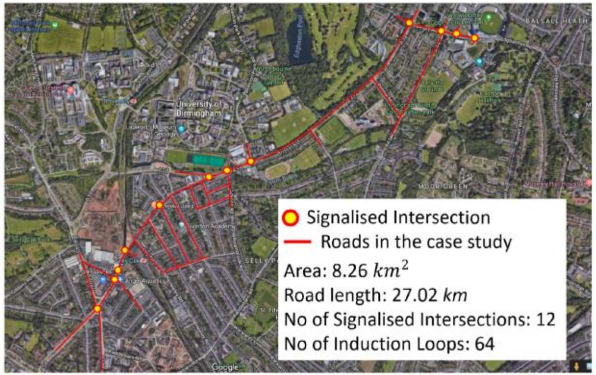


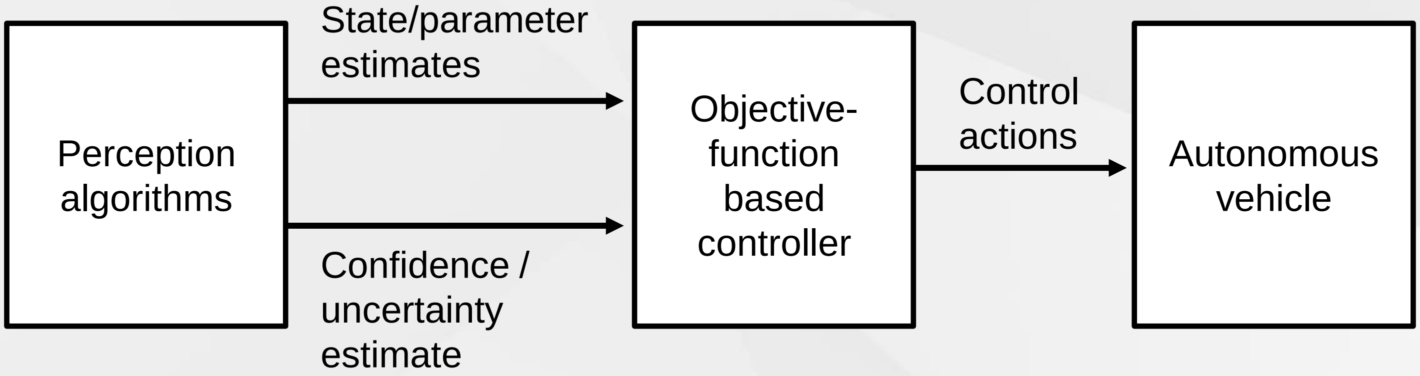
Fig. 9: Map of the simulated road network of Selly Oak (Birmingham, UK)

- Introduction:
  - What do I mean by ‘objective-based’ control?
  - Why do we care about uncertainty?

- Some methodologies and case studies:
  - Robust perception and sensing - road surface friction estimation from camera images
  - Control to meet objectives despite uncertainty - robust and stochastic MPC
  - What should the objectives be? – energy efficient ACC systems

- **Conclusion:**
  - **Some closing thoughts and open research questions**

Framework: objective-based control with uncertainty



Can we do this with current methods?

Conclusions and current challenges

- ML models for perception can estimate probabilities of states/parameters
  - *But… many methods aim for high accuracy, not good calibration of probabilities*

- There are now lots of methods for stochastic/robust MPC
  - *But… complex to implement, takes expert knowledge to design for each vehicle*

- Using economic objectives, controllers can save energy / increase range
  - *Can we also design objective functions that promote other goals, such as user acceptance, improved traffic flow, etc?*