

Controlling Stop and Go Traffic with a Single Autonomous Vehicle: Experimental Results

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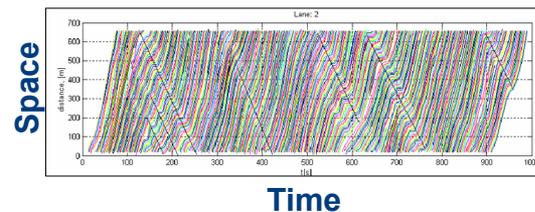
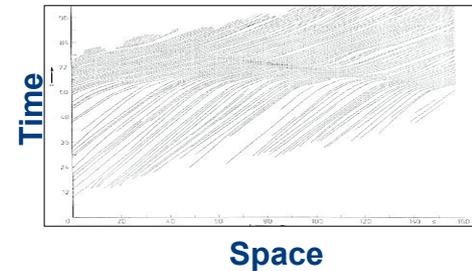
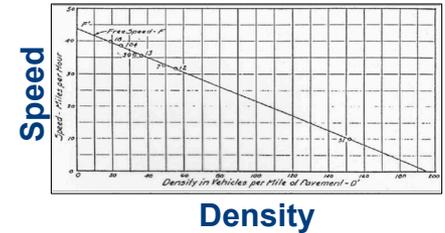
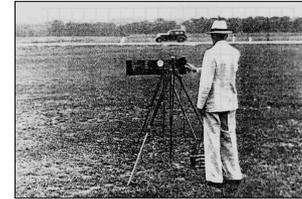


Shumo Cui
Hannah Pohlmann
Benjamin Seibold

Data drives understanding in transportation



- 1935 – Greenshields collected traffic data on highway
 - Density vs. Speed
- 1974 – Treiterer and Myers used aerial photography to track traffic waves
 - Tracking waves along the highway
- 2001 – PEMS dataset
 - Use inductive loop detectors for traffic counts
- 2003 – NGSIM data
 - Instrumental for calibration of microscopic traffic models for shock waves



Transformative datasets

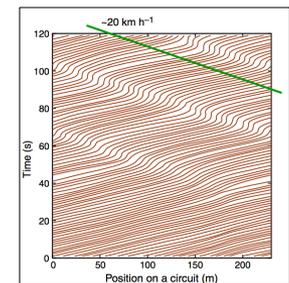


- 2006 – Naturalistic Driving Study
 - Collected vehicle data of naturalistic driving
- 2012 – U. Michigan V2V deployment
 - 2700+ V2V and V2I equipped vehicles and roadside units deployed in Ann Arbor, MI
- 2013 – New York City taxi dataset
 - Used to understand large-scale mobility in the city



2008 – Sugiyama, et al. experiment

Demonstrated that traffic waves emerge in absence of external bottlenecks



Autonomous vehicles have come a long way



Ford concept AV, 1962



DARPA Urban Grand Challenge, 2007



Tesla Model S Autopilot, 2015

- AV technology has reached a point where it is feasible to test on large scales

Questions: How will AVs behave in traffic with other human drivers? Can AVs be used to benefit human-piloted traffic? Need data to answer these questions.

How technology has shaped transportation



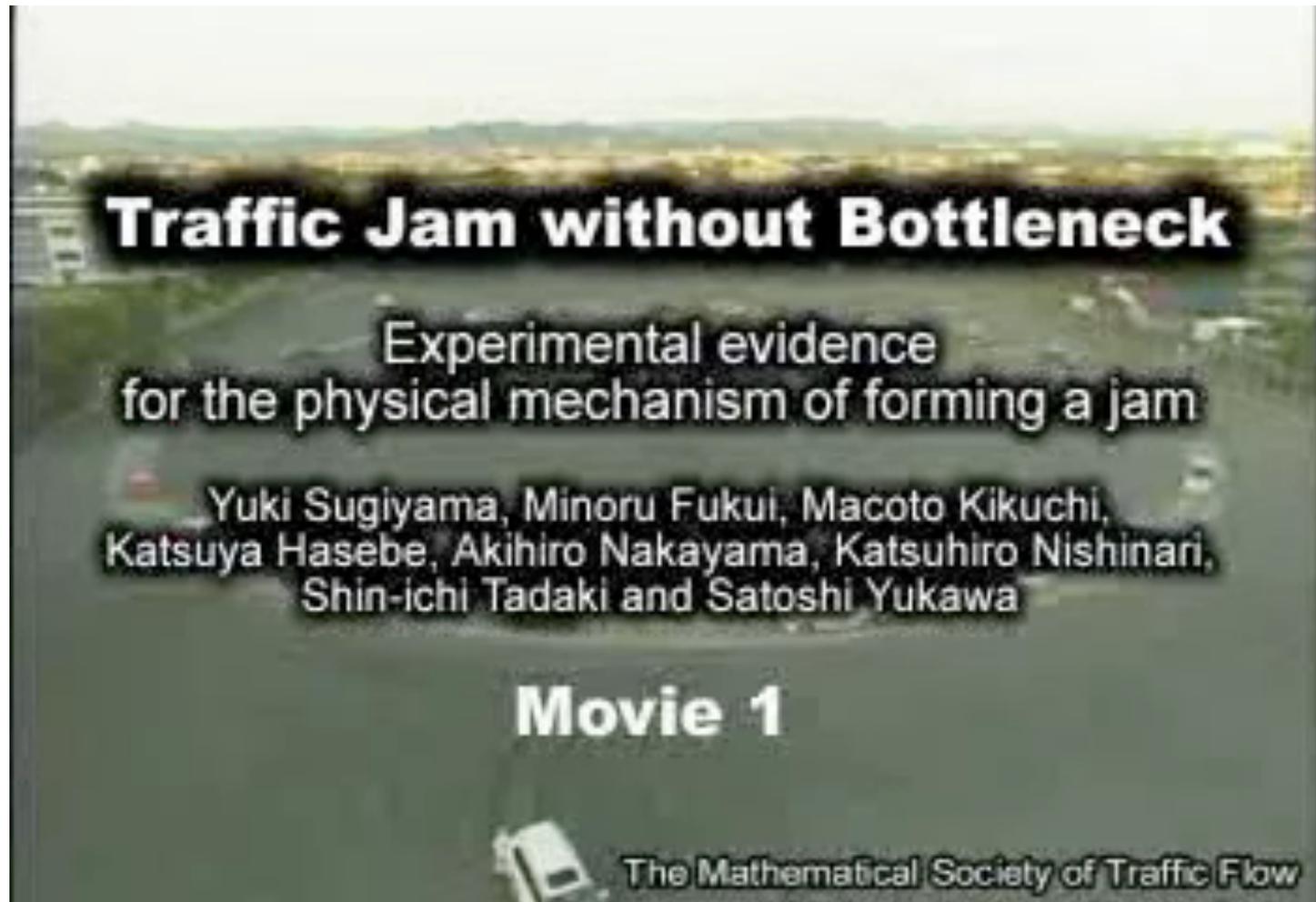
- Classical estimation **pre ~2010**
 - Dedicated sensors at fixed locations
- Modern estimation **today**
 - 1-5% GPS penetration



- Traffic control **today**
 - Dedicated actuation at fixed locations
- Future traffic control **~2020+**
 - Mobile actuation with a few autonomous vehicles



Traffic waves arise dynamically



[Sugiyama, et al., 2008]

Sugiyama: contributions and limitations



- Contribution
 - Demonstrated traffic waves arise in absence of external bottlenecks
- Limitations
 - No engine data recorded
 - No fuel consumption data recorded
 - Difficult to identify impact on fuel consumption



Experimental goals



Goal: collect data of oscillatory traffic that includes:

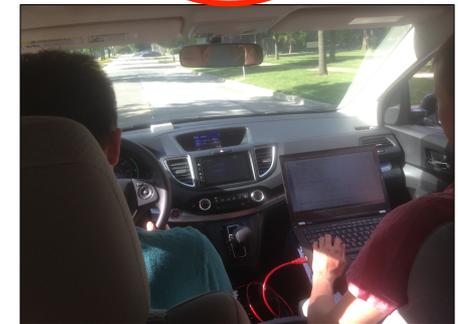
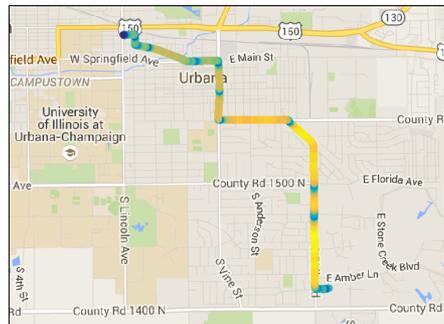
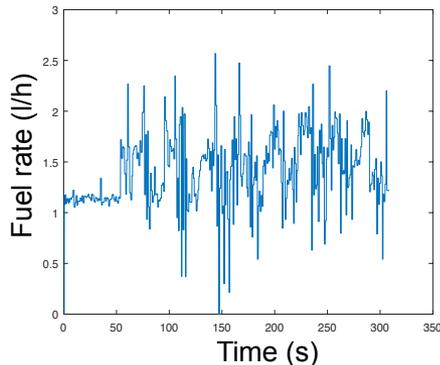
- Vehicle trajectories
- Fuel consumption
- Complete fleet information

Measuring vehicle performance



Goal: collect data on vehicle performance and fuel consumption to enable research on the link between oscillatory traffic and emissions.

- OBD-II scanners and tablets tested
- Can collect fuel consumption data



Key feature: collecting OBD-II data enables understanding of fuel consumption in oscillatory conditions

Collecting vehicle trajectories

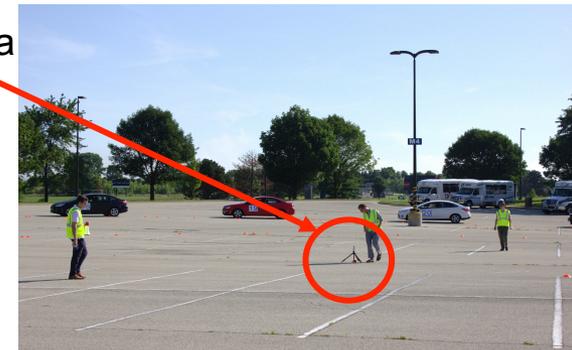


Goal: accurately track vehicle trajectories using a repeatable method.



Solution: Use a VSN360 360° panoramic camera to film experiments from the center of a circular track

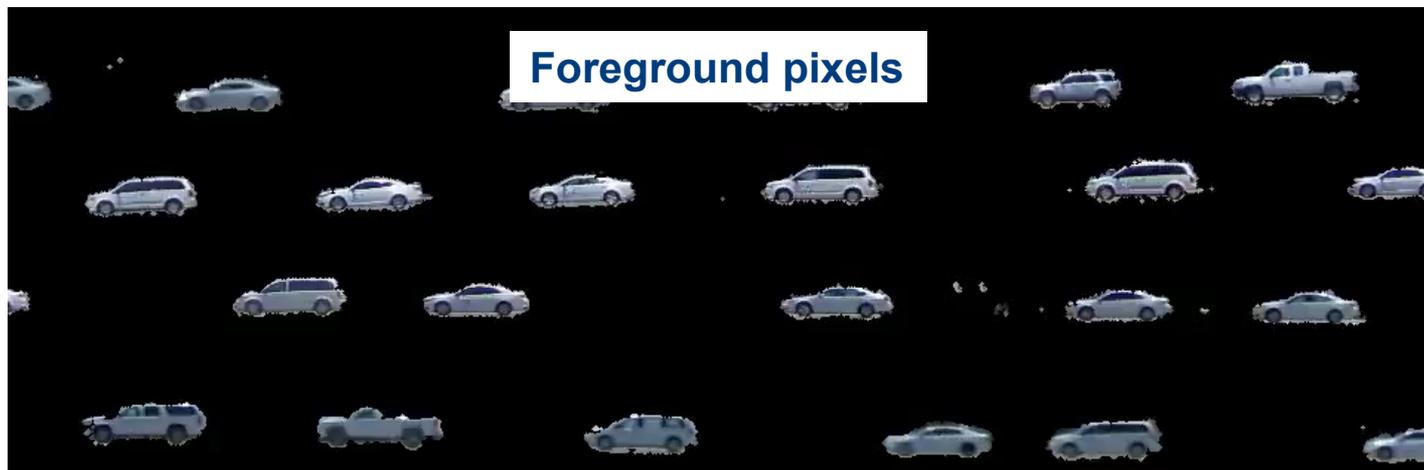
V360 camera



Extracting vehicle trajectories from 360 video



- Step 1: Identify Background
 - Filter moving pixels using *dense optical flow*
 - Subtract background image from each frame to find vehicle pixels

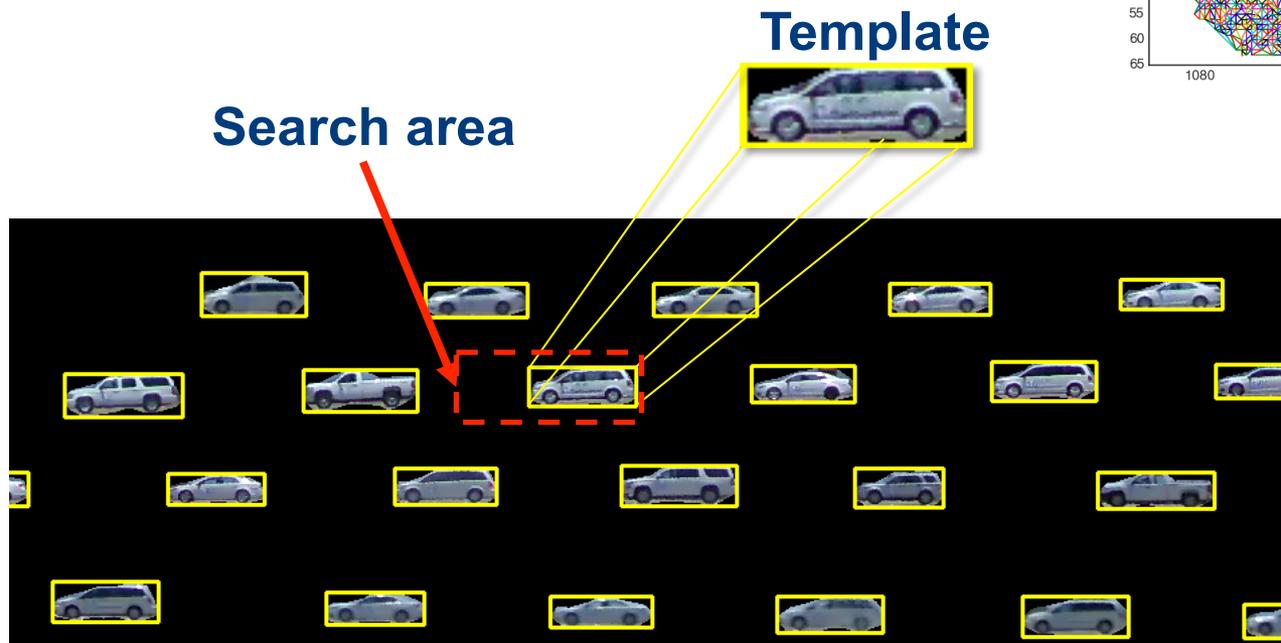
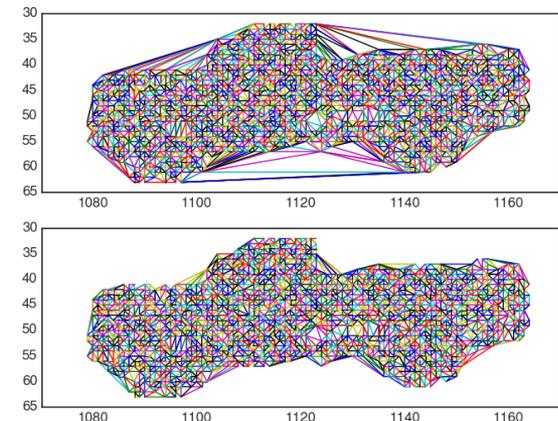


Extracting vehicle trajectories from 360 video

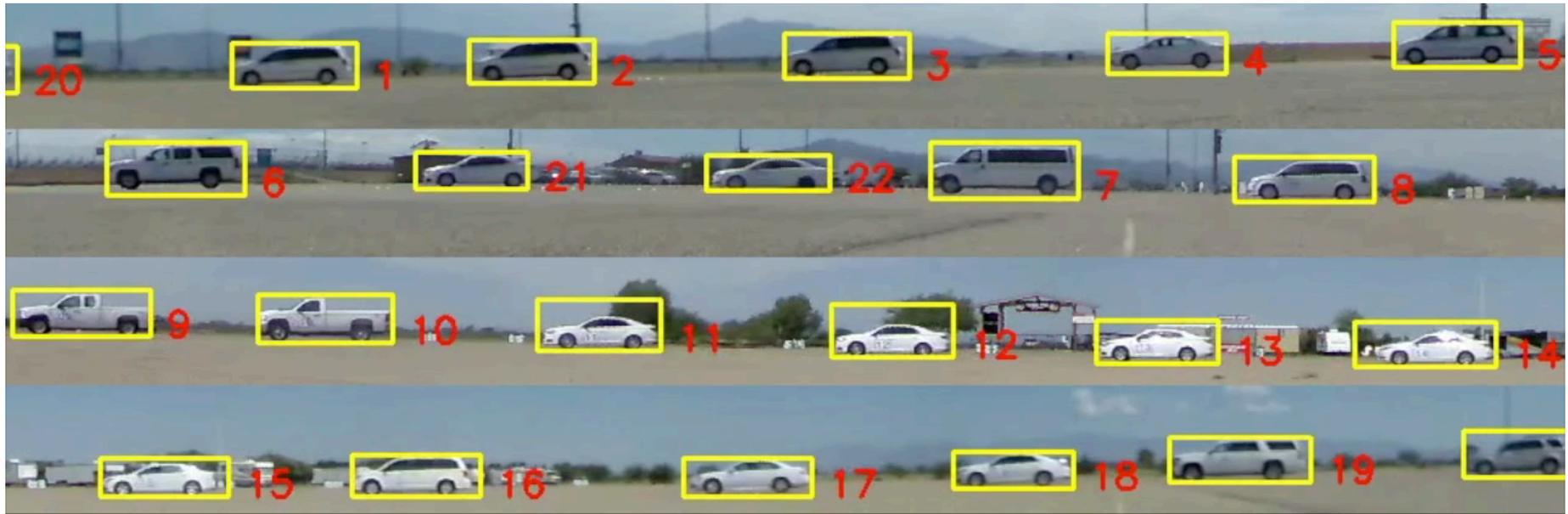


- Step 2: Cluster foreground pixels
 - Construct a template for each vehicle
- Step 3: Tracking
 - Match template frame by frame

Template refinement from pixel cluster



Extracting vehicle trajectories from 360 video



- Position Accuracy: 1.5 pixels (0.11 meters) matched with human-annotated data
- Velocity Accuracy: 0.09 m/s (0.2 mph)

Result: Computer vision enables precise vehicle tracking throughout the experiment

Experimental logistics

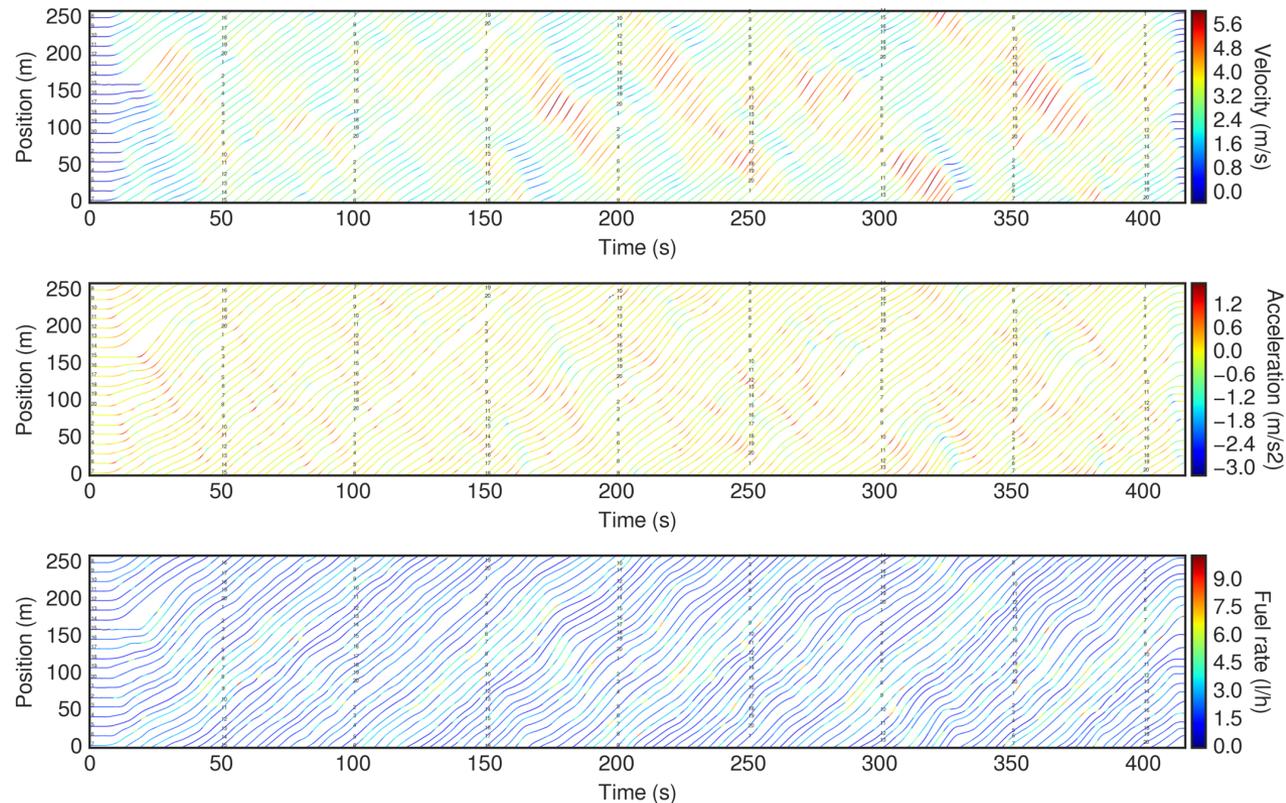


Total of 20 experiments conducted to re-produce traffic waves

Experimentally reproducing traffic waves



- Collected a total of 20 five to 10-minute experiments to observe traffic behavior
- Extracted vehicle trajectories and accelerations from video footage
- Collected OBD-II data (fuel consumption, engine speed, etc.) from all experiments



Contribution: Data demonstrates repeatability of traffic waves and enables systematic study of oscillatory traffic and affects on fuel consumption and emissions.

Can a single AV change the traffic state?



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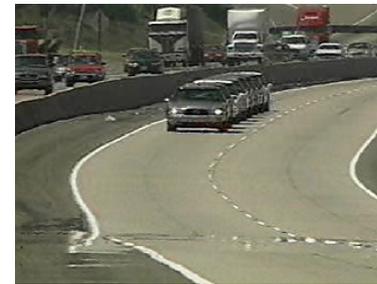
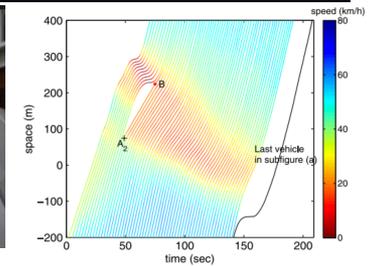
?

Question: Can an AV be used to dampen traffic waves and reduce fuel consumption and emissions?

Efforts in traffic control



- Single vehicle control
 - Motion planning; deep learning; etc.
- Variable speed limit control
 - Use VSL to dampen waves (e.g. SPECIALIST)
- Platooning
 - Connected and controlled cars, trucks, etc.
- Mixed traffic with AVs
 - Traffic signal free intersections; load balanced routing; simulating CACC and ACC technologies in the steam, etc.



COMPANION



[Shladover 1995; Ioannou et al. 1993; Buehler et al. 2009; He et al. 2017; Jin and Orosz 2014; Davis 2004; Besselink & Johansson, 2017; Hegyi et al. 2008; Rios-Torres & Malikopoulos 2016; Swaroop & Hedrick 1996; Talebpour & Mahmassani 2016]

Traffic string stability



Traffic string stability is defined in terms of how a perturbation from equilibrium is propagated upstream

Let $\Delta x = x_{j+1} - x_j$, consider a car following law

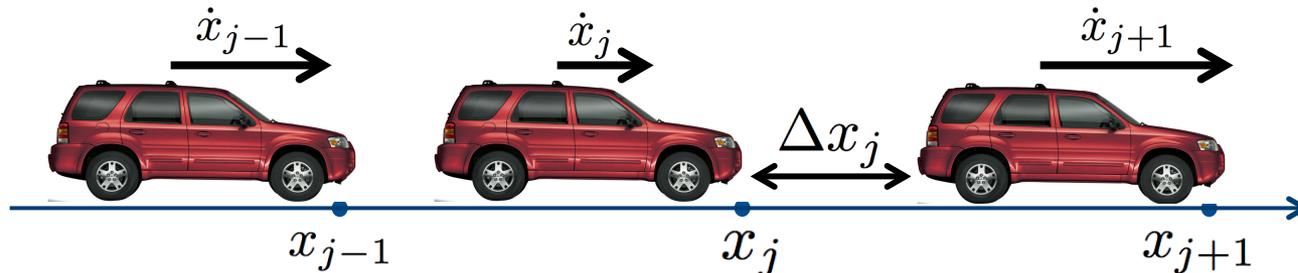
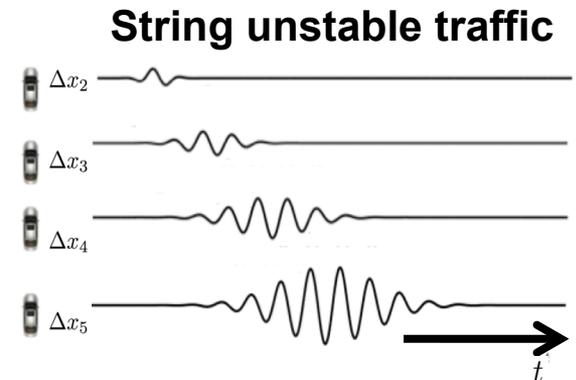
$$\ddot{x} = f(\Delta x_j, \dot{x}_{j+1} - \dot{x}_j, \dot{x}_j)$$

Compute perturbation growth rate

$$\lambda = \frac{\frac{\partial f}{\partial \Delta x_j}}{\left(\frac{\partial f}{\partial \dot{x}_j}\right)^3} \left(\frac{1}{2} \left(\frac{\partial f}{\partial \dot{x}_j}\right)^2 - \frac{\partial f}{\partial(\dot{x}_{j+1} - \dot{x}_j)} \frac{\partial f}{\partial \dot{x}_j} - \frac{\partial f}{\partial \Delta x} \right)$$

If $\lambda < 0$ the car following model is *string stable*

If $\lambda > 0$ the car following model is *string unstable*



Example model of human piloted traffic

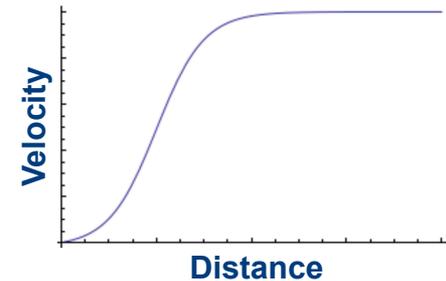


- Model of **human drivers**
Acceleration of vehicle j :

$$\ddot{x}_j = a \cdot (V(\Delta x_j) - \dot{x}_j) + b \cdot \frac{\dot{x}_{j+1} - \dot{x}_j}{\Delta x_j^2}$$

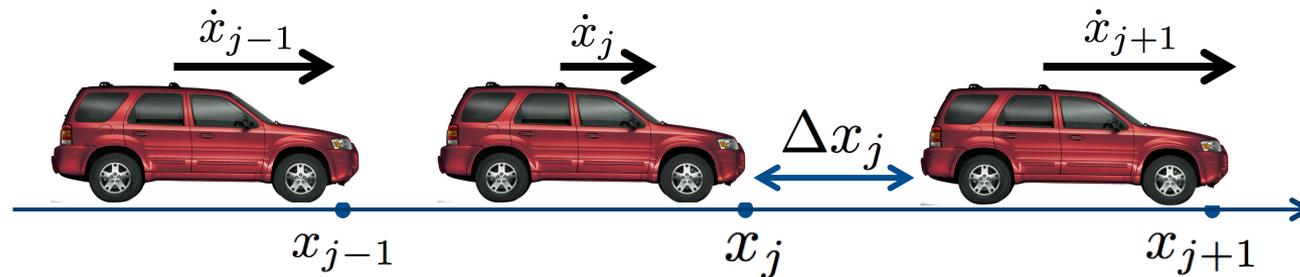
relax towards
optimal velocity

relax towards
leader's velocity



$$V(\Delta x_j) = V_m \frac{\tanh(\Delta x_j/d_0 - 2) + \tanh(2)}{1 + \tanh(2)}$$

$$\mathbf{z} = \begin{bmatrix} x_1 \\ \dot{x}_1 \\ x_2 \\ \dot{x}_2 \\ \vdots \\ x_N \\ \dot{x}_N \end{bmatrix}$$



Modelling human drivers

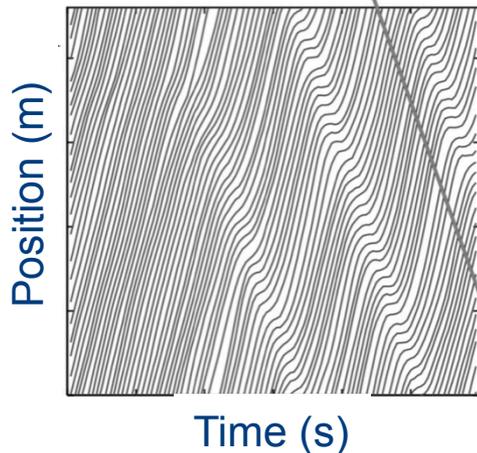


$$\ddot{x}_j = a \cdot (V(\Delta x_j) - \dot{x}_j) + b \cdot \frac{\dot{x}_{j+1} - \dot{x}_j}{\Delta x_j^2}$$

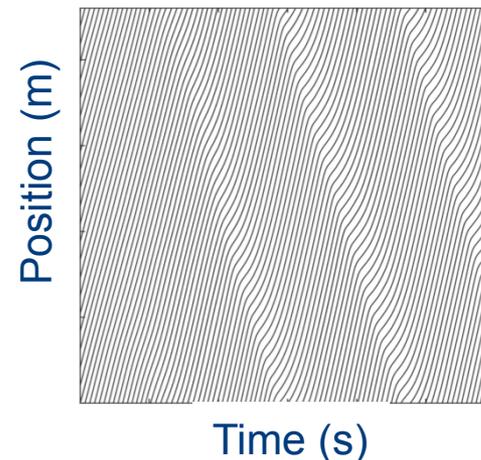
relax towards optimal velocity relax towards leader's velocity

Calibrate model parameters using parameter sweep to match macroscopic properties of data from Sugiyama, et al.:

Vehicle trajectories
(Sugiyama et al. 2008)



Vehicle trajectories
(simulation)



Stability analysis continued



- Linear *string stability* analysis around equilibrium flow of calibrated OV-FTL model:

$$\ddot{x}_j = a \cdot (V(\Delta x_j) - \dot{x}_j) + b \cdot \frac{\dot{x}_{j+1} - \dot{x}_j}{\Delta x_j^2}$$

Compute partial derivatives

$$\frac{\partial f}{\partial \Delta x_j} = aV_m \frac{\operatorname{sech}^2\left(2 - \frac{\Delta x_j}{d_0}\right)}{2 + 2\tanh(2)}$$

$$\frac{\partial f}{\partial (\dot{x}_{j+1} - \dot{x}_j)} = \frac{b}{\Delta x_j^2}$$

$$\frac{\partial f}{\partial \dot{x}_j} = -a$$

- Stability depends on sign of: $\lambda = \frac{\frac{\partial f}{\partial \Delta x_j}}{\left(\frac{\partial f}{\partial \dot{x}_j}\right)^3} \left(\frac{1}{2} \left(\frac{\partial f}{\partial \dot{x}_j} \right)^2 - \frac{\partial f}{\partial (\dot{x}_{j+1} - \dot{x}_j)} \frac{\partial f}{\partial \dot{x}_j} - \frac{\partial f}{\partial \Delta x} \right)$
- In case of calibrated OV-FTL model: $\lambda = 0.60 > 0$

Calibrated OV-FTL model is unstable

Feedback control of the AV



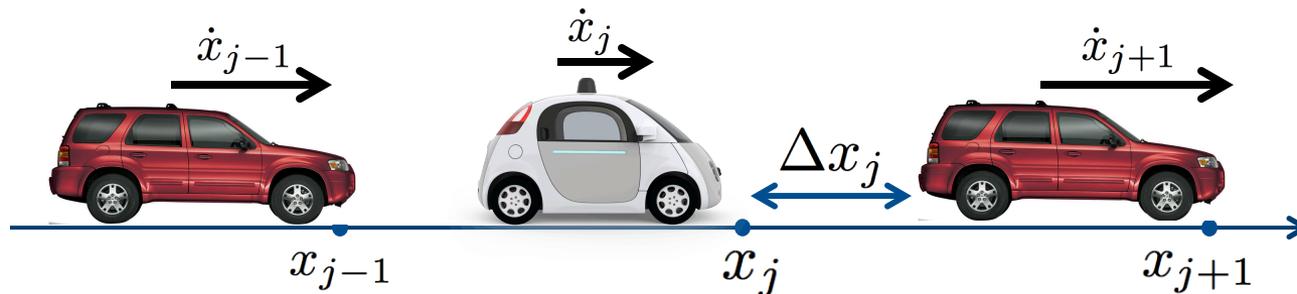
- Model of an **autonomous vehicle**
Acceleration of vehicle j :

$$\ddot{x}_j = a \cdot (V(\Delta x_j) - \dot{x}_j) + b \cdot \frac{\dot{x}_{j+1} - \dot{x}_j}{\Delta x_j^2} + c \cdot (u_{\text{eq}} - \dot{x}_j)$$

relax towards
optimal velocity

relax towards
leader's velocity

relax towards
equilibrium velocity



- Small deviations from human driving
- Stability of traffic flow depends on the entire system

A possible stabilizing control



$$\ddot{x}_j = \underbrace{a \cdot (V(\Delta x_j) - \dot{x}_j)}_{\text{relax towards optimal velocity}} + \underbrace{b \cdot \frac{\dot{x}_{j+1} - \dot{x}_j}{\Delta x_j^2}}_{\text{relax towards leader's velocity}} + \underbrace{c \cdot (u_{eq} - \dot{x}_j)}_{\text{relax towards equilibrium velocity}}$$

relax towards
optimal velocity

relax towards
leader's velocity

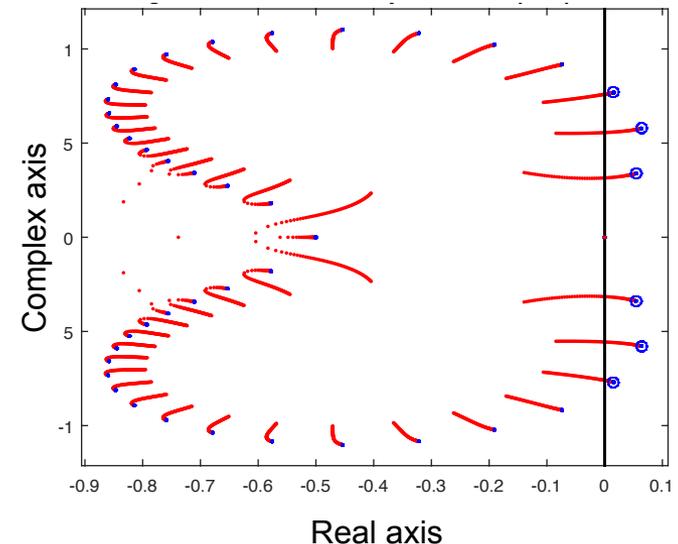
relax towards
equilibrium velocity

$$\begin{cases} \dot{\mathbf{z}} = \mathbf{A}\mathbf{z} + \mathbf{B}u \\ u = \mathbf{F}\mathbf{z} - u_{eq} \end{cases}$$

Only control velocity of AV

$$\mathbf{B} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \quad \mathbf{F}^\top = \begin{bmatrix} 0 \\ -c \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

- Linearize system about equilibrium
- Determine gain required to stabilize the system around the equilibrium



Intuition: AV drives with as constant a speed as possible.

Experimental testbed: CAT Vehicle



- Used the University of Arizona *Cognitive Autonomous Test (CAT) Vehicle*
- Fully-autonomous Ford Escape Hybrid
- Possible to test control algorithms in Gazebo simulation and in the field



Experimentally demonstrate wave dampening



Vehicle decals



Driver briefings



Tech setup



Fuel consumption loggers



Temperature: **107 F**
25 vehicles
30 drivers
15 support staff
280 bottles of water
15 cans of sun screen
19 experiments



Safety checks



Managing the CAT Vehicle



Experiment adjustments



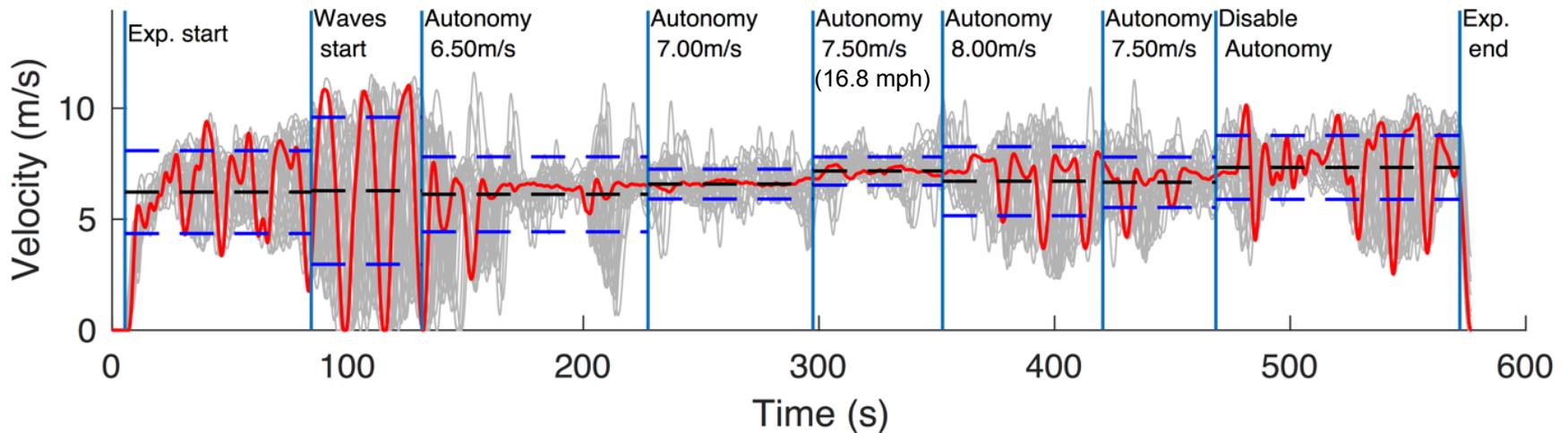
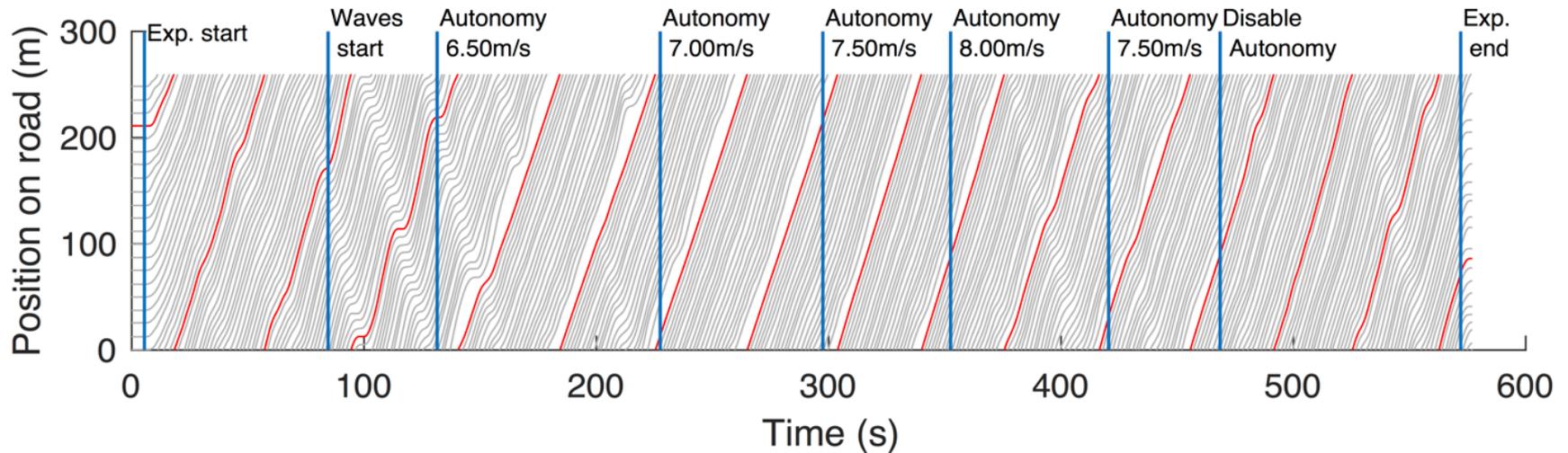
Staff meetings



Dissipation of stop-and-go traffic waves via control of a single autonomous vehicle



Experimental results



Total velocity standard deviation: **80.8%** ↓

Fuel consumption: **42.5%**



Total braking events: **98.6%** ↓

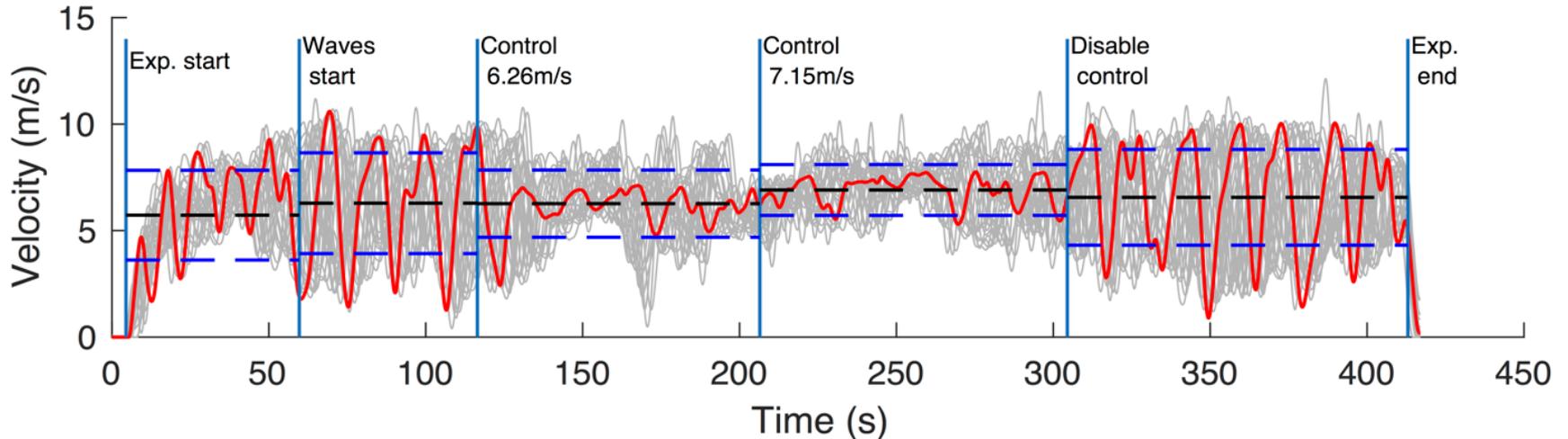
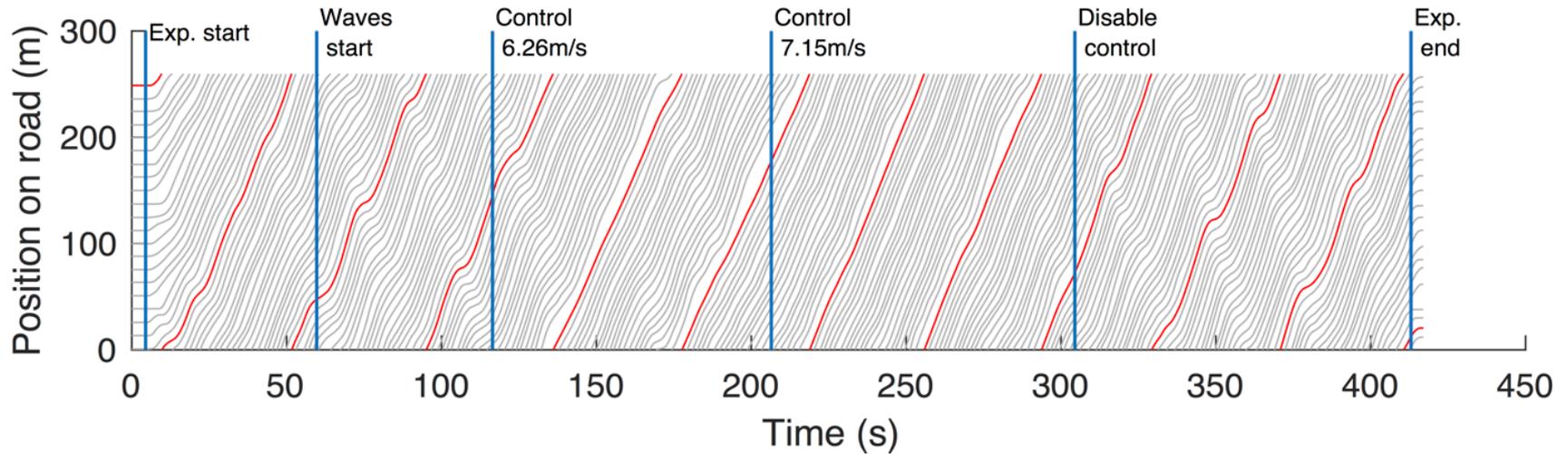
Throughput: **14.1%** ↑

Experimental results: Robot Matt



Control algorithm: instruct Robot Matt via two-way radio to drive with a constant speed.

Experimental results: Robot Matt



Total velocity standard deviation: **49.5%** ↓

Fuel consumption: **22.1%**



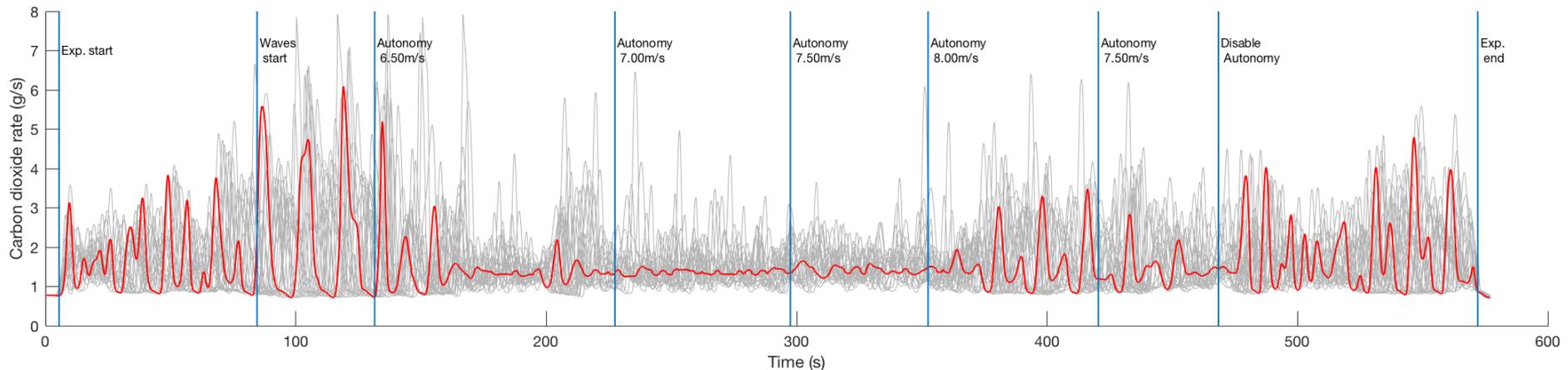
Total braking events: **76.2%** ↓

Throughput: **9.8%** ↑

Evaluating emissions reduction



- How does stop-and-go traffic influence emissions?
- Detailed trajectories enables emissions estimation
- Use the VT-Micro model to estimate emissions based on each vehicle's velocity and acceleration



Carbon dioxide: **21.1** ↓

Carbon monoxide: **12.5%** ↓

Hydrocarbons: **16.2%**



Summary



- Designed experimental protocol to observe oscillatory traffic
- Designed controller to stabilize traffic flow
- Demonstrated wave dampening in simulation and in an experiment
- Investigated impact on emissions



Special thanks to the experimental crew: Shumo Cui, Maria Laura Delle Monache, Rahul Bhadani, Matt Bunting, Miles Churchill, Nathaniel Hamilton, R'mani Haulcy, Hannah Pohlmann, Fangyu Wu, Benedetto Piccoli, Benni Seibold, Jonathan Sprinkle, and Dan Work.

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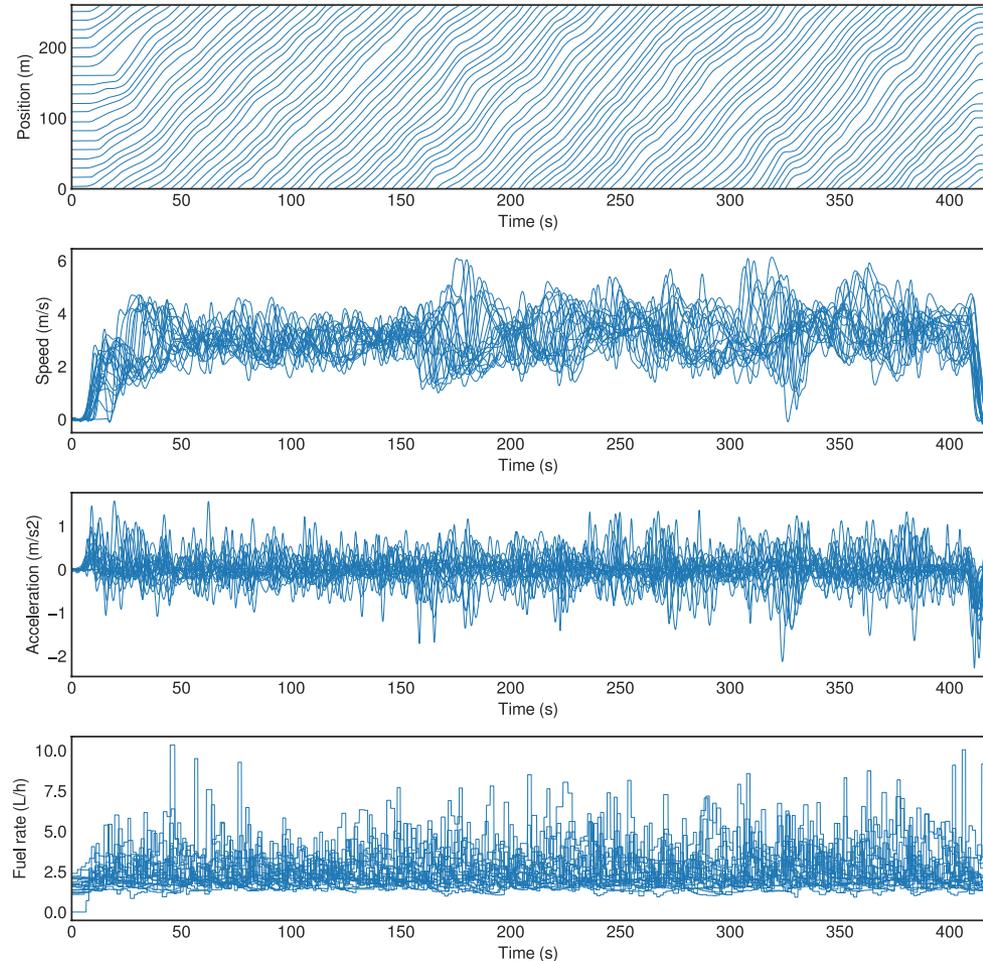


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Experimentally reproducing traffic waves



- Collected a total of 20 5 to 10-minute experiments to observe traffic behavior
- Extracted vehicle trajectories and accelerations from video footage
- Collected OBD-II data (fuel consumption, engine speed, etc.) from all experiments



Contribution: Data demonstrates repeatability of traffic waves and enables systematic study of oscillatory traffic and affects on fuel consumption and emissions.

Wave dampening controller



Goal: command the AV to drive at the desired velocity, U

Consider three regions:

1. A safe region where $v^{\text{cmd}} = U$
2. A stopping region, where zero velocity is commanded
3. An adaptation region (in two parts), where average of lead vehicle and desired velocity is commanded

$$v^{\text{cmd}} = \begin{cases} 0 & \text{if } \Delta x \leq \Delta x_1 \\ v \frac{\Delta x - \Delta x_1}{\Delta x_2 - \Delta x_1} & \text{if } \Delta x_1 < \Delta x \leq \Delta x_2 \\ v + (U - v) \frac{\Delta x - \Delta x_2}{\Delta x_3 - \Delta x_2} & \text{if } \Delta x_2 < \Delta x \leq \Delta x_3 \\ U & \text{if } \Delta x_3 < \Delta x \end{cases}$$

$$v = \min(\max(v^{\text{lead}}, 0), U)$$

$\Delta x_1, \Delta x_2, \Delta x_3$, are safety distance parameters

