Traffic Flow Theory in the Era of Autonomous Vehicles

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Outline

• From individual driving to traffic flow
• Prominent features of traffic flow
• Models of traffic flow-human driven vehicles
• Models of traffic flow-autonomous vehicles
• The future of traffic flow
The Driving Task as Feedback Control

Actual System:
Road Environment
Traffic Environment

Measurements:
\{ (x', y'), g', R' \}, \ v', \ s'

Control Law:
Direction/Lane
Speed/Spacing

Vehicle Dynamics
Traffic Dynamics

Disturbances
Boundary cond.

{(x, y), g, R}, v, s, ...
Human Drivers vs Autonomous Vehicles From A Control Perspective

**Human Drivers**
- Sensing is imprecise but more versatile
- Response is slower but more robust
- Best at processing fuzzy information and is highly adaptive
- Strength: handles complex tasks such as lane tracking, obstacle avoidance more easily

**Autonomous Vehicles (Robo Cars)**
- Sensing is more precise but less versatile
- Response is faster but less robust
- Best at exercising precise controls and is less adaptive:
- Strength: handles procedural tasks such as speed control, car following more easily
The Essence of Traffic Flow Theory is to Infer

• The Speed-Spacing Control Law of Each Driver

\[ v_n(t) = \{?\}(s_n(t), \ldots, E) \]

\[ E = \{\text{speed limits, grades, radius, surface conditions, visibility, \ldots}\} \]

• And the collective dynamics of an OPEN “Many-Particle” Dynamical System with “random” insertions and removals (reflecting LANE CHANGE interactions) controlled by these driver control laws

\[ \{x_n(t) = v_n(t), n=1,2,\ldots,N\} \]
Example: The California Motor Code Rule

• For every 10 mph of speed, leave one car length of space

• This translates to

\[ s(t) - l = v(t)/10 \equiv T v(t) \]

or

\[ v(t) = s(t) - l/T \]

with speed limits

\[ v(t) = \min\{V_{\downarrow} f, s(t) - l/T \} \]
If Human Drivers are Identical Robots

with super fast reaction time and vehicles capable of infinite acceleration and deceleration

• Micro model

\[ \begin{align*}
x(t) &= v(t) \\
v(t) &= a(t) \\
a(t) &= \begin{cases} 0, & T, v(t) < V_{\downarrow f} \\
V_{\downarrow f} @ u(t) - v(t)/T, & v(t) \geq V_{\downarrow f} \end{cases}
\end{align*} \]

• Traffic Stream Model (steady-state)

\[ V(s) = \min\{V_{\downarrow f}, s/T\} \]

• Macro (continuum) model (in vehicle coordinate)

\[ s_{\downarrow t} - v_{\downarrow n} = 0, \ v = V(s) \]
What are These Models and what phenomena do they produce?

• Micro model: “linear” CF model of Pipes
  • Acceleration waves
  • Deceleration waves

• Stream model: Triangular FD
  • Capacity: 2640 pcphpl (l=20ft, T=1.36sec, Vf=60mph)
  • Jam wave speed: -10 mph

• Macro model: LWR with Triangular FD
  \[ k \frac{\partial t}{} + Q \frac{\partial x}{(k)} = 0 \]
  • Shock waves
  • Expansion (acceleration) waves
The slope of the jam wave speed is a good indicator whether drivers of different type of vehicles follow the same driving rule or not.
In reality, human drivers

• Differ from each other in driving ability and habits
• Cannot assess motion and distances precisely
• Respond with delay and finite acceleration/deceleration
• Do not follow rules exactly

Consequence:

Traffic flow in the real world is much more complex
Prominent Features of Real Traffic Flow

- Phase transitions
- Nonlinear waves
- Stop-and-Go Waves (periodic motion)
Phase transitions
Nonlinear waves

Vehicle platoon traveling through two shock waves

flow-density phase plot
Stop-and-Go Waves (Oscillations)

Scatter in the phase diagram is closely related to stop-and-go wave motion.
Some Classical Traffic Models

• Microscopic
  • Modified Pipes’ model
  • Newell’ Model
  • Bando’ model

• Macroscopic continuum
  • LWR model
  • Payne-Whitham model
  • Aw-Rascle, Zhang model

\[ \rho(t) = \min \left\{ v_f \left( s_n(t) - l \right) / \tau \right\} \]
\[ \rho(t + \tau) = v_f \left[ 1 - \exp \left\{ -\lambda \left( s_n(t) - l \right) / v_f \right\} \right] \]
\[ \rho(t) = a \left[ \left( u_0(s_n) - \rho(t) \right) \right], a = 1 / \tau \]

\[ \rho = 1 / s, u_*(s) = v_*(\rho), q = \rho v, q_*(\rho) = \rho v_*(\rho) \]

\[ \rho_t + q_*(\rho)_x = 0 \]
\[ \rho_t + (\rho v)_x = 0, \quad v_t + (vv)_x + \frac{c_0^2}{\rho} \rho_x = \frac{v_*(\rho) - v}{\tau} \]
\[ \rho_t + (\rho v)_x = 0, \quad v_t + (v - c(\rho)) v_x = \frac{v_*(\rho) - v}{\tau} \]

\[ c(\rho) = -\rho v_*(\rho) \]

• v-s (speed-spacing) relation is central to all these models
The Difficulty of Modeling Real Flow

• Each driver is different
• Driving rules are hidden
• Sensing is imprecise
• Behavior is adaptive, nonlinear, and perhaps inconsistent
• (Driving environment is complex)
When Robo Cars Take Over the Road

• Behavior is uniform and consistent
• Sensing and control is more precise
• Rules are always obeyed
• (Driving environment is still complex)

More importantly, driving rules are by design, leaving rooms for optimizing flow and safety

Feedback Control Problem
Traffic Flow Theory For Robo Cars - Longitudinal Control

- Example RoboCar#1
  \[ a(t+\tau) = k\downarrow r \{V(s) - v\}, V(s) = \min\{V\downarrow f, s/T\} \]

- Human: \( \tau = 1-2s, T = 1.36-2s \); Robo Car: \( \tau = 0.4-0.6s, T = 0.8-1.2s \), Capacity: \( \approx 1/T', +70\% \),

- But this may be too rosy a prediction in the initial deployment stage (liability)
Example RoboCar#2

\[ a(t + \tau) = k_{\downarrow r} \{ V(s) - v \} + k_{\downarrow v} \{ u - v \} \]

Faster response and higher throughput than RoboCar#1

\[ \tau = 0.4-0.6s, \ T = 0.6-0.75s \]
Example RoboCar#3 (RoboCar#2 with V2V)

\[ a(t + \tau) = k\downarrow a \downarrow u(t) + k\downarrow r \{V(s) - v\} + k\downarrow v \{u - v\} \]

And the list goes on: you can come up with other models that meet safety and stability requirements.
Expected throughput with vehicle platooning

Throughput of CACC platooning with different platoon size and intra-platoon time gap setting
Future of Traffic Flow Theory Research (1)

• Do the Arrival of Robo Cars Mean The End of Traffic Flow Research?
  • Automation creates uniformity and standardization, suppresses randomness: From billions of drivers to a handful: Google Car, GM Car, Toyota Car ....
  • Behavior of each Robo Car is consistent and known

From Human Drivers to Robots
Future of Traffic Flow Theory Research (2)

• In the short term
  • design of driving models for Robo cars
  • Robo car friendly infrastructure

• In the intermediate term
  • Mixed traffic with Robo Cars,
  • Platooning of Robo Cars
  • Lightless intersections with in-vehicle signal control
  • Rich micro level data for understanding and modeling traffic, and validating traffic models
Future of Traffic Flow Theory Research (3)

• In the long term, full automation of highway traffic
  • Optimal scheduling and pricing for congestion free networks
  • Robust Recovery from Disruptions

• New services and shared use of autonomous vehicles
  • Robo Taxi Services
  • Last and first-mile of transit (flexible transit)
  • Seamless integration of multiple modes
  • And the list goes on
Concluding Remarks

Autonomous Vehicles will

• In the long run bring more order to traffic flow and simplify traffic flow theory

• Produce rich data for traffic flow research

• Brings a host of brand new research problems for modeling, design and operations of transportation systems