Improving bus arrival-time estimates

using real-time vehicle positions to estimate road state

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1. Introduction

- position tracking well studied, e.g., Kalman Filter [1–3], particle filter [4], etc.
- estimating and predicting road state (i.e., travel time along roads) less developed, particularly for bus prediction
- several papers use other vehicles *on the same route* [5], but no generic attempt to model travel times independently of route
- many public transport providers don't use any form of traffic model, instead relying on scheduled stop times (often inaccurate, don't respond to real-time events)

2. GTFS network construction

- **GTFS** is an API specification for transit APIs [6]
- available in over 500 locations worldwide
- therefore, a general approach to 'segmenting' the network is required

1. raw GTFS data provides **one shape per route**
2. **identify points of intersection** between one or more routes using algorithm adapted from [7]
3. **split shapes at intersections** to obtain shapes for each individual road segment
4. express each route as a sequence of road segments

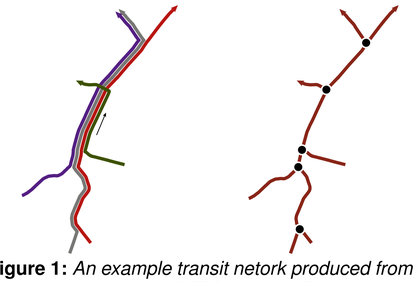

Figure 1: *An example transit netork produced from five routes. Left: the raw GTFS shapes; Right: the generated transit network with intersections shown as dots.*

- Implementation in progress: the `gtfsnetwork` R package, github.com/tmelliott/gtfsnetwork

3. Vehicle state model

- sequential Bayesian methods well suited to **real-time vehicle tracking**
- **particle filter**: general, flexible estimation method that uses sample of particles $\tilde{\boldsymbol{X}}_k = (\boldsymbol{X}_k^{(i)})_{i=1}^N$, allowing it to handle **multimodality** (e.g., when passing bus stops) and **assymetry** (e.g., bus cannot go backwards)
- measurement function $h : \mathbb{R} \mapsto \mathbb{R}^2$ calculates map (GPS) position of each particle based on distance traveled along shape

1. predict trajectory of each particle using transition function f and system noise parameter Q_k

$$\boldsymbol{X}_k^{(i)} = f(\boldsymbol{X}_k^{(i)}, w_k), \quad w_k \sim N(0, Q_{k-1})$$

2. assume $\boldsymbol{Y}_k$ is a noisy measurement of true position with GPS error σ_y^2, and define $g : \mathbb{R}^2 \mapsto \mathbb{R}^2$ such that $dist(g(\boldsymbol{Y}_1), g(\boldsymbol{Y}_2))$ is the ground distance between the points, then the measurement model is

$$g(\boldsymbol{Y}_k) \sim N\left(g(h(\boldsymbol{X}_k)), \begin{bmatrix} \sigma_y^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix}\right)$$

and $(\delta_k^{(i)})^2 = dist(g(h(\boldsymbol{X}_k^{(i)})), g(Y_k))^2$ is the sum of two independent normal r.v.'s with mean 0 and variance σ_y^2

$$\left((\delta_k^{(i)})^2 / \sigma_y^2\right) \sim \chi^2(2) \sim \text{Exp}(0.5)$$

3. evaluated the likelihood for each particle

$$p(\boldsymbol{Y}_k | \boldsymbol{X}_k^{(i)}) = 0.5 e^{-(\delta_k^{(i)})^2 / 2\sigma_y^2}$$

4. update state by resampling particles with replacement, using likelihood weights

$$w^{(i)} = p(\boldsymbol{Y}_k | \boldsymbol{X}_k^{(i)}) / \sum_{j=1}^{N} p(\boldsymbol{Y}_k | \boldsymbol{X}_k^{(j)})$$

5. use resulting trajectories to estimate vehicle speed along road segments to update network in section 4

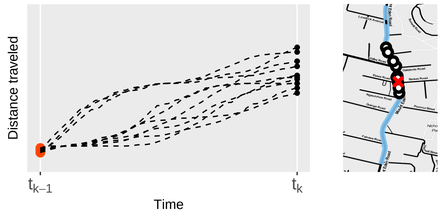

Figure 2: *Left: simulated particle trajectories. Right: particle positions $h(\boldsymbol{X}_k^{(i)})$; observation $\boldsymbol{Y}_k$ in red.*

Figure 3: *$\boldsymbol{Y}_k$ (red cross) is a bivariate normal r.v. with mean and variance represented by the black dot and concentric rings, respectively.*

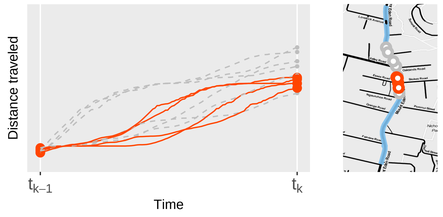

Figure 4: *After resampling, a posterior sample of trajectories is obtained (orange).*

4. Network state model

- using an adapted extended Kalman filter (EKF) to model network state
- segment j has state β_r^j (vehicle speed) at time t_r with variance P_r^j
- Step 1: predict future state
  - define **transition function** a such that the state converges to the prior (fig. 5)
  - prior mean speed $\mu_j(t)$ and variance $\psi_j(t)$ at time t from **historical data** (blue lines in fig. 5)
  - use EKF equations to recursively predict state in 1 second intervals
  - define **system noise** so P_r^j converges to $\psi_j(t_r)$
- Step 2: update state when observations recieved from step 5 in section 3 (red point fig. 6)
  - **measurement error:** variance of particle speeds
  - use EKF update equations to update state at time of observation

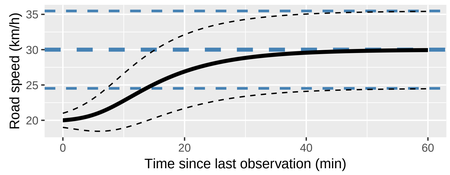

Figure 5: *Road state $\hat{\beta}^j$ (with variance P_r^j, dashed black lines) converge to the prior (blue lines).*

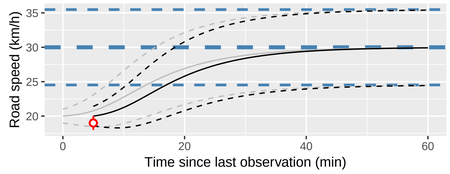

Figure 6: *After recieving a vehicle speed estimate (red dot), the state is updated.*

5. Predicting arrival time

- for each particle, simulate journey along remainder of route
- **simulate speed** $v_t^j \sim N(\hat{\beta}_t^j, P_t^j)$ for each upcoming segment j
- simulate intersection and bus stop wait times and compute arrival time at each upcoming stop
- resulting ETA distribution can be conveyed to passengers
  - a point estimate
  - and/or a prediction interval (for commuters, this would be understood as a min and "max" wait time)
- ETAs are typically reported in discrete minutes. For the example in figure 7, the distribution might be summarised with
  - a **point estimate** of 5 minutes
  - a **prediction interval** of 4–8 minutes
- summary statistics need to be chosen such that, as the bus approaches, the estimates decrease

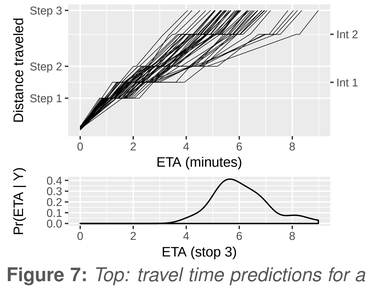

Figure 7: *Top: travel time predictions for a bus, showing locations of stops (left axis) and intersections (right axis). Bottom: posterior density of ETAs for stop 3.*

6. Conclusion and future work

- segmenting routes into route-independent segments allows vehicle observations to update the road network
- real-time network state used to predict arrival time

Next steps:

- improve the network state model: variable speeds along a roads (i.e., $\mu_j(t, d)$ depends on time and distance along segment), include covariates in state transition (adjacent segments, yesterday's traffic, weather, etc.)
- develop a stop-time and intersection-wait time model to more accurately predict wait times
- investigate ideal summary statistics for ETAs (both point and interval prediction)

References

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