

The method behind: Mobile device tracking and transportation mode detection

NTTS 2019, Brussels Yvonne Gootzen, Marco Puts

Center for Big Data Statistics

Introduction

Method applicable for:

- ► Observations at time steps
- ► Noisy observations of locations
- ▶ Different transportation models

Applications

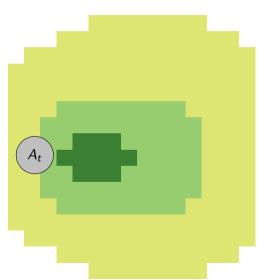
Examples:

- ▶ Object tracking in video
- ► Mobile Network connections
- ► Radar observations

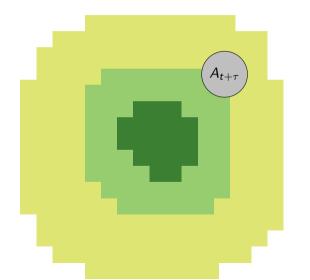


▶ Two observations: A_t , $A_{t+\tau}$

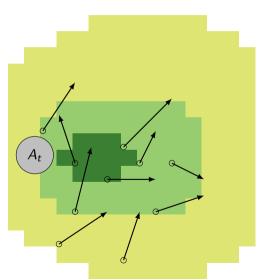




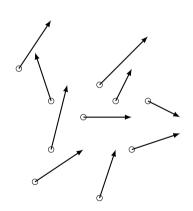
- ▶ Two observations: A_t , $A_{t+\tau}$
- ▶ Each with different $\mathbb{P}(|\mathsf{location}|A)$



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- ▶ Two observations: A_t , $A_{t+\tau}$
- ▶ Each with different $\mathbb{P}(|a|A)$
- ▶ Particles $p_1(t), ..., p_{10}(t)$



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$$p_i(t) = egin{pmatrix} x_i(t) \ y_i(t) \ v_i(t) \ heta_i(t) \end{pmatrix}$$

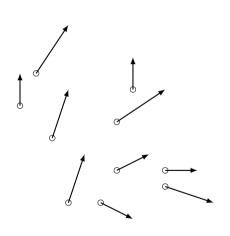
- ▶ Horizontal position: $x_i(t)$
- ▶ Vertical position: $y_i(t)$
- ▶ Velocity: $v_i(t)$
- ▶ Direction: $\theta_i(t)$



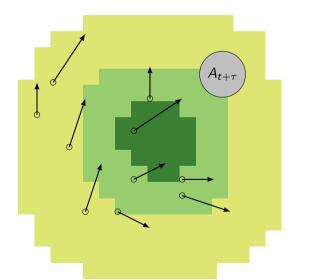
- ► Prediction step
- ightharpoonup Time step duration: au

$$ilde{p_i}(t\!+\! au) = egin{pmatrix} x_i(t) + au \cdot \cos(heta) \cdot v_i(t) \ y_i(t) + au \cdot \sin(heta) \cdot v_i(t) \ v_i(t) + u_v \ heta_i(t) + u_ heta \end{pmatrix}$$

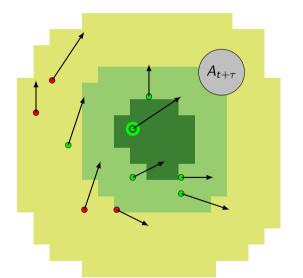
- $\triangleright u_v$ (stabilising) random update
- $\triangleright u_{\theta}$ random update



Particles $\tilde{p_1}(t+ au),...,\tilde{p_{10}}(t+ au)$

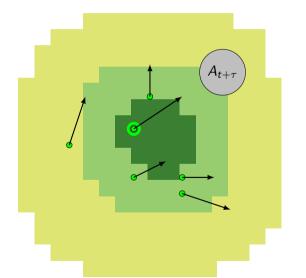


▶ Observation $A_{t+\tau}$

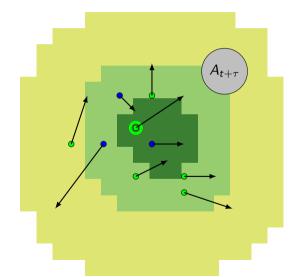


- ▶ Observation $A_{t+\tau}$
- ▶ Sample $p_1(t+\tau),...,p_7(t+\tau)$

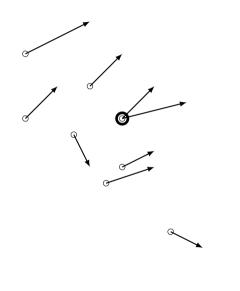
$$egin{aligned} &
ho_1(t+ au),...,
ho_7(t+ au) \ & \in \{ ilde{
ho_1}(t+ au),..., ilde{
ho_{10}}(t+ au)\} \end{aligned}$$

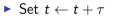


- ▶ Observation $A_{t+\tau}$
- ▶ Sample $p_1(t + \tau), ..., p_7(t + \tau)$
- ▶ Drop $\tilde{p}_i(t + \tau)$



- ▶ Observation $A_{t+\tau}$
- ▶ Sample $p_1(t + \tau), ..., p_7(t + \tau)$
- ▶ Drop $\tilde{p}_i(t + \tau)$
- Sample $p_8(t+\tau)$, $p_9(t+\tau)$ and $p_{10}(t+\tau)$ from observed probabilities $\mathbb{P}(|\text{location}|A_{t+\tau})$





► Repeat cycle

Summarising particles



- ▶ Particles $p_1(t), ..., p_{10}(t)$
- ▶ Horizontal position: $x_i(t)$
- ▶ Vertical position: $y_i(t)$
- ▶ Velocity: $v_i(t)$
- ▶ Direction: $\theta_i(t)$

Summarising particles



▶ Particles $p_1(t),, p_{10}(t)$	Summarise
▶ Horizontal position: $x_i(t)$	•
▶ Vertical position: $y_i(t)$	•
▶ Velocity: $v_i(t)$	•
▶ Direction: $\theta_i(t)$	•

Summarising particles: path



- ▶ Particles $p_1(t), ..., p_{10}(t)$
- ▶ Horizontal position: $x_i(t)$
- Vertical position: $y_i(t)$
- ▶ Velocity: $v_i(t)$
- ▶ Direction: $\theta_i(t)$

- Summarise
- Position
- Position

Summarising particles: transportation mode



- ▶ Particles $p_1(t), ..., p_{10}(t)$
- ▶ Horizontal position: $x_i(t)$
- ▶ Vertical position: $y_i(t)$
- ▶ Velocity: $v_i(t)$
- ▶ Direction: $\theta_i(t)$

- Summarise
- Position
- Position
- ► Transportation mode
- ► Transportation mode

Transportation mode detection

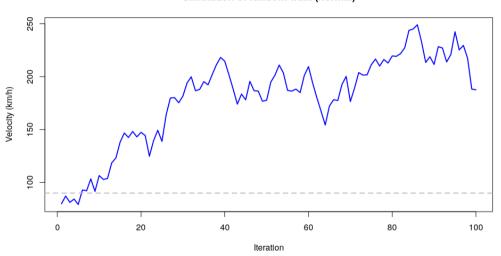
Updating velocity and direction

Transportation mode detection

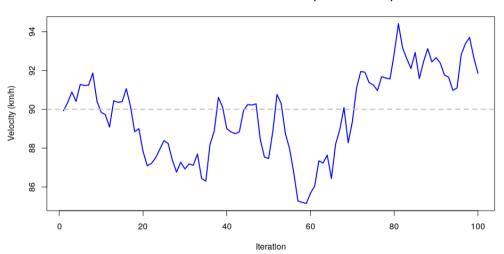
Updating velocity and direction

► Focus: velocity

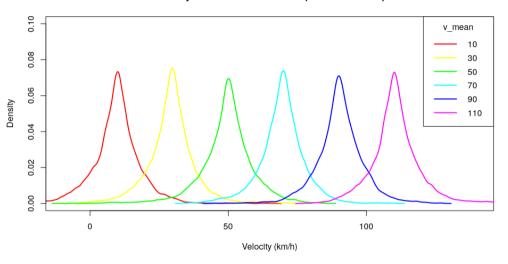
Simulation of random walk (normal)



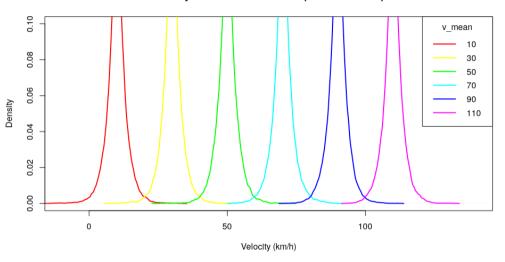
Simulation of stable random walk (skewed normal)



Density of stable random walk (skewed normal)



Density of stable random walk (skewed normal)



Transportation mode detection

- ► Modelled mode: velocity and direction updates
- Mode profile: survival ratio of modelled modes over time
- Designed to resemble transportation mode
- ▶ Transportation mode detection: based on mode profile

Conclusion

Building block between raw data and further analysis.

Advantages:

- Compatible with any observation model
- Use information over time
- ► Transportation mode detection

Disadvantages:

- ► Simulation dependent
- Computational costs