

Inertial Odometry on Handheld Smartphones

Arno Solin¹ Santiago Cortés¹ Esa Rahtu² Juho Kannala¹

¹Aalto University ²Tampere University of Technology

21st International Conference on Information Fusion

July 12, 2018

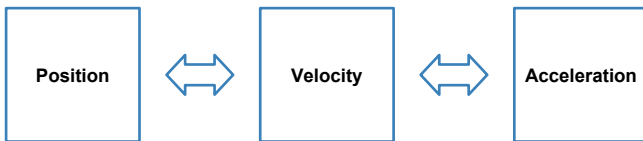
Introduction

- ▶ Phones have **accelerometers** and **gyroscopes**
- ▶ Should in theory enable **inertial navigation**
- ▶ **Cheap** and **small** sensors
- ▶ **Low quality** data
 - ➔ inertial navigation not possible
- ! We demonstrate that it can be done



Inertial navigation: How it should work

- ▶ Velocity is the integral of acceleration.
- ▶ Position is the integral of velocity.
- ▶ We can observe acceleration and angular velocity in the mobile phone.



Inertial navigation: Why it does not work

- ▶ All inertial navigation systems suffer from **integration drift**.
- ▶ Small **errors** in the measurement of acceleration and angular velocity...
- ▶ Progressively larger **errors** in velocity...
- ▶ Even greater **errors** in position.

- ▶ The dominating component in acceleration is gravity.
- ▶ Even slight error in orientation makes the gravity **'leak'**.

- ▶ The sequential nature of the problem makes the **errors accumulate**.

Inertial navigation: How to make it work

- ▶ Input: **accelerometer** data \mathbf{a}_k and **gyroscope** data $\boldsymbol{\omega}_k$.
- ▶ Accelerometer and gyroscope biases part of the state:

$$\tilde{\mathbf{a}}_k = \mathbf{T}_k^{\mathbf{a}} \mathbf{a}_k - \mathbf{b}_k^{\mathbf{a}} \quad \tilde{\boldsymbol{\omega}}_k = \boldsymbol{\omega}_k - \mathbf{b}_k^{\boldsymbol{\omega}}$$

- ▶ Dynamical model:

$$\begin{pmatrix} \mathbf{p}_k \\ \mathbf{v}_k \\ \mathbf{q}_k \end{pmatrix} = \begin{pmatrix} \mathbf{p}_{k-1} + \mathbf{v}_{k-1} \Delta t_k \\ \mathbf{v}_{k-1} + [\mathbf{q}_k(\tilde{\mathbf{a}}_k + \boldsymbol{\varepsilon}_k^{\mathbf{a}}) \mathbf{q}_k^* - \mathbf{g}] \Delta t_k \\ \boldsymbol{\Omega}[(\tilde{\boldsymbol{\omega}}_k + \boldsymbol{\varepsilon}_k^{\boldsymbol{\omega}}) \Delta t_k] \mathbf{q}_{k-1} \end{pmatrix}$$

for position \mathbf{p}_k , velocity \mathbf{v}_k , and orientations \mathbf{q}_k at time t_k .

- ▶ Inference by an **Extended Kalman filter** / smoother

Inertial navigation: How to make it work

- ▶ Additional **constraints** (observations) are required
- ▶ This framework can use
 - ▶ Zero-velocity updates (ZUPTs)
 - ▶ Position fixes
 - ▶ Loop-closures
 - ▶ Barometric air pressure for relative height
- ▶ A **pseudo-measurement** keeping the velocity component from exploding
- ▶ Sensor **timing** info
- ▶ A matter of learning the **biases**

How does this compare to previous approaches?

On mobile devices PDR typically based on:

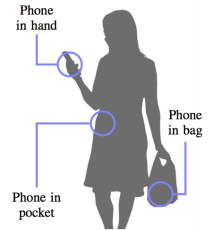
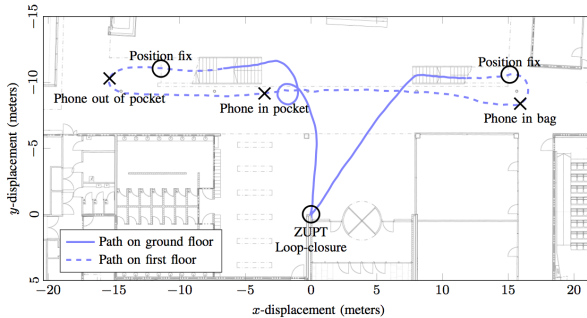
- ▶ Movement detection
- ▶ Step and heading systems
- ▶ Visual features
- ▶ All of these are limited in some way



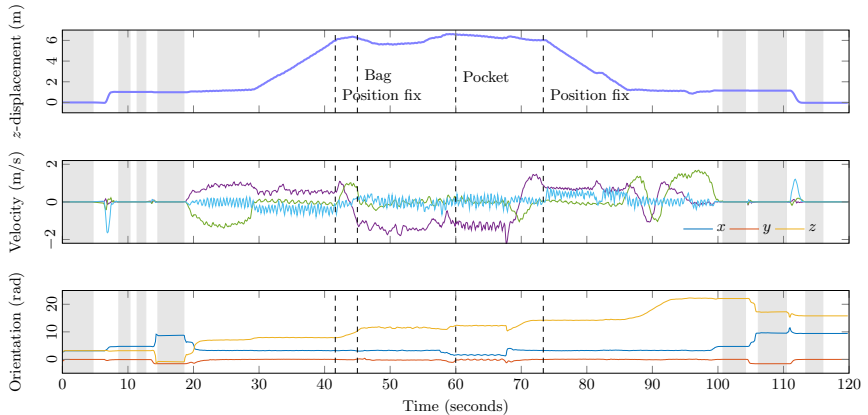
Example studies

- ▶ Equipment used:
 - Off-the-shelf iPhone 6
- ▶ Sensors:
 - Built-in gyroscope and accelerometer
 - Sampling rate: 100 Hz
- ▶ Computations:
 - Off-line
(runnable on device hardware)

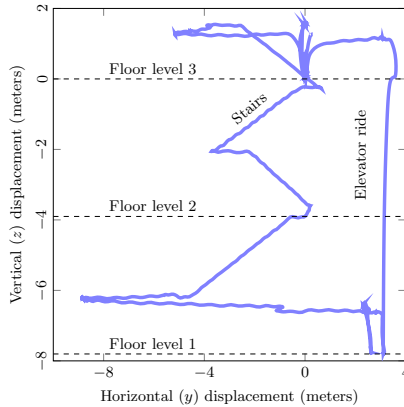
Example: Conventional PDR



Example: Conventional PDR



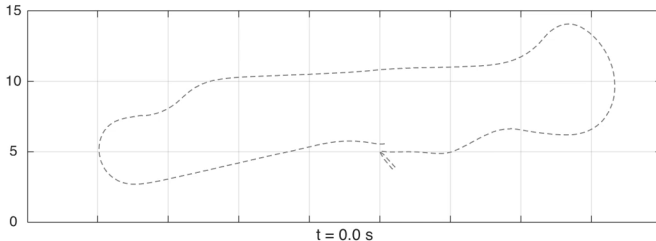
Example: Conventional PDR



Example: General dead-reckoning

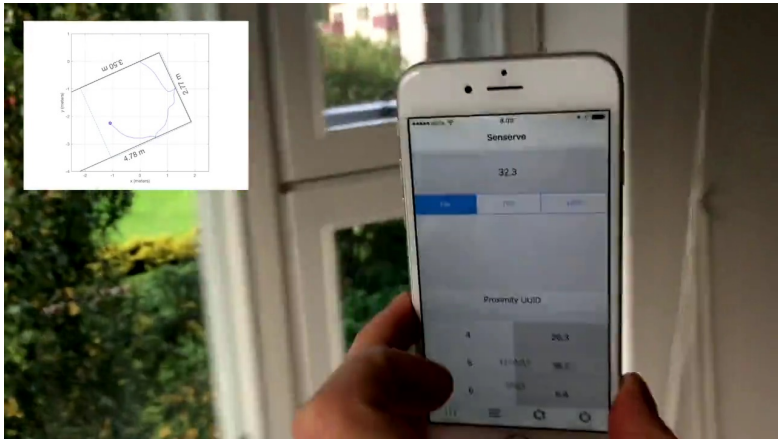


Example: General dead-reckoning



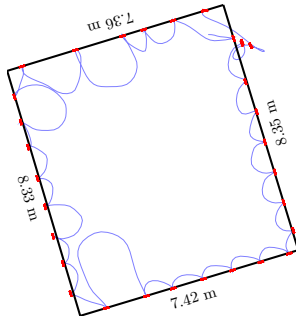
The video is available on YouTube:
<https://youtu.be/L-E9fNsrvII>

Example: Inertial measurements

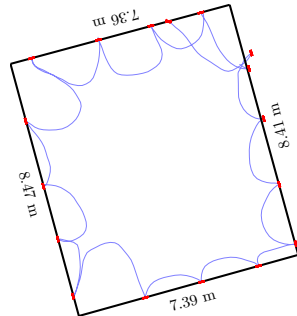


The video is available on YouTube:
<https://youtu.be/L-E9fNsrvII>

Example: Inertial measurements



(a) Measurement #1



(b) Measurement #2

Recap

- ▶ Inertial navigation on a smartphone **is possible**
- ▶ The key is learning the sensor transformations (**biases**)
- ▶ Not possible without measurements (**constraints**)
 - ZUPTs
 - pseudo-speed
- ▶ Future work towards relaxing these further



- ▶ Homepage:
<http://arno.solin.fi>
- ▶ Twitter:
[@arnosolin](#)