IMU Dataset For Motion and Device Mode Classification

Parinaz Kasebzadeh,
Gustaf Hendeby, Carsten Fritsche,
Fredrik Gunnarsson, Fredrik Gustafsson.

Automatic Control
Department of Electrical Engineering
Linköping University

LINKÖPING UNIVERSITY

LINKÖPING
UNIVERSITY

Introduction

Pedestrian navigation systems using IMUs are gaining increasing interest as a tool to improve the localization aspects

- Problem: these systems are not self-contained navigation systems.

Introduction

Pedestrian navigation systems using IMUs are gaining increasing interest as a tool to improve the localization aspects

- Problem: these systems are not self-contained navigation systems.
- Solution: added supporting information, we use
  - learning gait parameters adaptively
  - information about mobile users activity mode and device modes to improve the learning process.

Introduction

Pedestrian navigation systems using IMUs are gaining increasing interest as a tool to improve the localization aspects

- Problem: these systems are not self-contained navigation systems.
- Solution: added supporting information, we use
  - learning gait parameters adaptively
  - information about mobile users activity mode and device modes to improve the learning process.
- Goal: Motion and Device modes classifications.

Introduction

Modes classification

- Supervised learning of classifiers requires labeled training data.
- Training data must be extensive and cover
  - various physical attributes.
  - various motion and device modes.
  - different environmental situations.

Introduction

Modes classification

- Supervised learning of classifiers requires labeled training data.
- Training data must be extensive and cover
  - various physical attributes.
  - various motion and device modes.
  - different environmental situations.
- Our data meets all aforementioned requirements. It is available from:

  http://users.isy.liu.se/en/rt/parka23/research.html

Introduction

TABLE : Motion-Device mode Classification

Device Mode \ Motion Mode	Standing Still (SS)	Walking (W)	Running (R)
Fixed hand (1)	Class SS	Class W1	Class R1
Swinging hand (2)		Class W2	Class R2
Pocket (3)		Class W3	Class R3
Backpack (4)		Class W4	Class R4

- Motion mode: can select a set of appropriate internal parameters in the PNS; step length and step detection thresholds.
- Device mode: can be used to better utilize the sensor.

LINKÖPING UNIVERSITY

Experiment Description

- **Measurement scenarios**
  - Case 1: Outdoor-only, Standing Still, Walking and Running
  - Case 2: Outdoor-indoor, Walking
  - Case 3 & Case 4: Outdoor-indoor, Standing Still, Walking and Running
- **Participants**
  - 6 Male
  - 2 Female

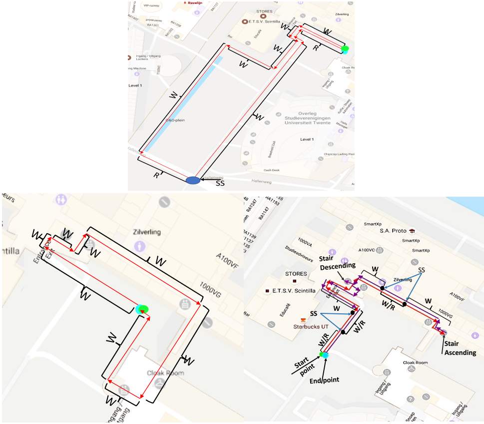


Figure: Measurement Scenarios. [Upper] Case 1, [Lower left] Case 2, [Lower left] Case 3

Available measurements

- **Sensors**
  - Xsens MVN Motion Capture,
  - Smartphone Nexus 5
- **Measurement specifications**
  - Accelerometer(Both)
  - Gyroscope(Both)
  - Magnetometer(Both)
  - Barometer (Both, Not processed in MVN)
  - GPS (Phone)
- **Measurement types**
  - Raw sensory data (Both)
  - Virtual IMU data from Body model (MVN)

Dataset Description

- The dataset containing all the introduced scenarios.
- The logged data from the phones and the MVN are extracted with 100 Hz and 60 Hz.
- All data are merged into one '.mat'-file
- File contains the data structure and attributes corresponding to each subject.
- Data is labeled.
- Example, measurements for Case 4 are in `Case4` and `Case4.Subject(1)` provides the all data for subject 1.

The dataset is available from
`http://users.isy.liu.se/en/rt/parka23/research.html`

LINKÖPING UNIVERSITY

Classification Evaluation

Classification Steps

- **Feature extraction on the raw signals**; A way to bring out the inherent information in the available data in better way, and reduce the dimensionality of the raw data to be able to apply classification algorithms.

Classification Evaluation

Classification Steps

- **Feature extraction on the raw signals**; A way to bring out the inherent information in the available data in better way, and reduce the dimensionality of the raw data to be able to apply classification algorithms.
- **Classification**; As a final step in characterizing the data, a classifier is applied to the features to try extract the motion and device modes.

Feature Extraction

Dividing the inertial data in sliding windows of 50 and 30 samples for phone and motion trackers, respectively, with no overlap.

Features:

- Signal Norm
- Signal Energy
- Signal Variance
- Frequency Analysis

Feature Extraction

Signal Norm

For a generic signal S, $\|S\|_{\max}$ denotes the max norm over the sliding window,

$$\|S\|_{\max} = \max_{n} \|S[n]\|.$$

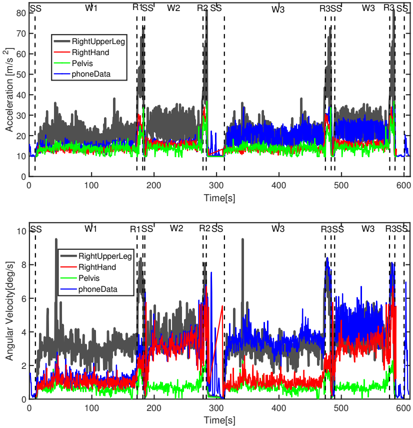


Figure: Signal norm for 4 different motion trackers together with the signal from the smartphones. [Upper] Accelerometer norm of signal. [Lower] Gyroscope norm of signal.

Feature Extraction

Signal Energy

$S[n]$ is a generic signal, a single accelerometer or gyroscope direction or norm is

$$E_S = \frac{1}{N}\sum_{n=0}^{N-1} S[n]^2.$$

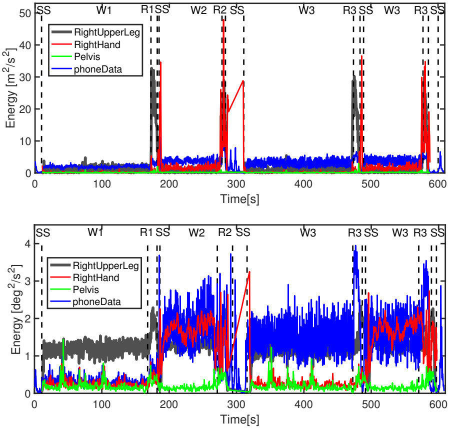


Figure: Signal norm for 4 different motion trackers together with the signal from the smartphones. [Upper] Accelerometer energy signal. [Lower] Gyroscope energy signal.

Feature Extraction

Signal Variance

For any generic signal $S[n]$ the average of the squared differences from the mean is

$$\sigma_S^2 = \frac{1}{N-1}\sum_{n=0}^{N-1}\left(\|S[n]\| - \mu_s\right)^2,$$

$$\mu_s = \frac{1}{N}\sum_{n=0}^{N-1}\|S[n]\|.$$

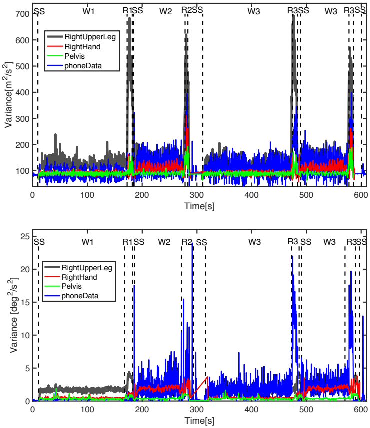
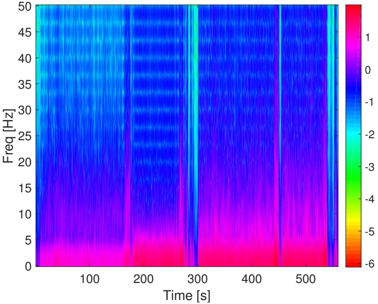


Figure: Signal norm for 4 different motion trackers together with the signal from the smartphones. [Upper] Accelerometer signal variance. [Lower] Gyroscope signal variance.

Feature Extraction

Frequency Analysis

To identify any movement such as periodic movement from aperiodic ones.



Classification

Classifier evaluation

- Two datasets, are formed for phone and motion tracker signals, separately.
- Each set contains eight features constructed from four signal attributes for both gyroscope and accelerometer.
- A supervised learning approach is applied.
- A multivariate decision tree classifier is trained using MATLAB; Machine learning toolbox.
- The classifier is validated with 10-fold cross-validation.

Classification

Classification results

TABLE : Confusion matrix of the modes classification represented in Table I using the binary decision tree classifier using cross-validation with 10 folds. The table shows how different annotated activities are classified in [%].

(a) Data from 4 different motion trackers

Annotated activity \ Recognised activity	R1	R2	R3	R4	SS	W1	W2	W3	W4
R1	83	8	0	6	0	0	0	0	0
R2	5	72	1	0	0	0	0	1	0
R3	0	2	96	0	0	0	0	0	0
R4	5	0	0	85	1	0	0	0	1
SS	0	2	0	1	79	2	0	0	1
W1	0	0	1	1	5	78	1	0	13
W2	0	8	0	0	0	1	84	6	0
W3	7	8	1	3	2	1	13	92	0
W4	0	0	1	4	13	17	1	0	84

(b) Data from phones.

Annotated activity \ Recognised activity	R1	R2	R3	R4	SS	W1	W2	W3	W4
R1	58	3	0	0	0	0	0	2	0
R2	1	60	4	4	0	0	1	2	0
R3	0	13	83	0	1	0	0	0	0
R4	20	3	0	56	0	0	0	2	0
SS	1	0	6	0	84	4	3	2	1
W1	3	0	0	7	7	83	3	1	8
W2	1	3	6	7	2	1	77	14	0
W3	14	17	2	22	1	1	16	75	0
W4	0	0	0	4	5	11	1	0	90

LINKÖPING UNIVERSITY

Summary

- An extensive dataset introduced for classification and investigation of the motion and device mode for PNS.
- All data are fully annotated with ground truth classes, and other metadata such as position and accurate full body motion.
- Discussed how the motion and device mode relate to PDR algorithms.
- Features have been extracted and a standard classifier applied to the dataset.
- Results form the classifier are promising but that research is need to improve the results further.

Summary

The presented dataset is available from:
`http://users.isy.liu.se/en/rt/parka23/research.html`

We hope the research community can benefit from it to further improve classification of device and motion mode using it.

Thank you!
Questions?!

www.liu.se

LINKÖPING UNIVERSITY