AN ONLINE FEATURE SELECTION ARCHITECTURE FOR HUMAN ACTIVITY RECOGNITION

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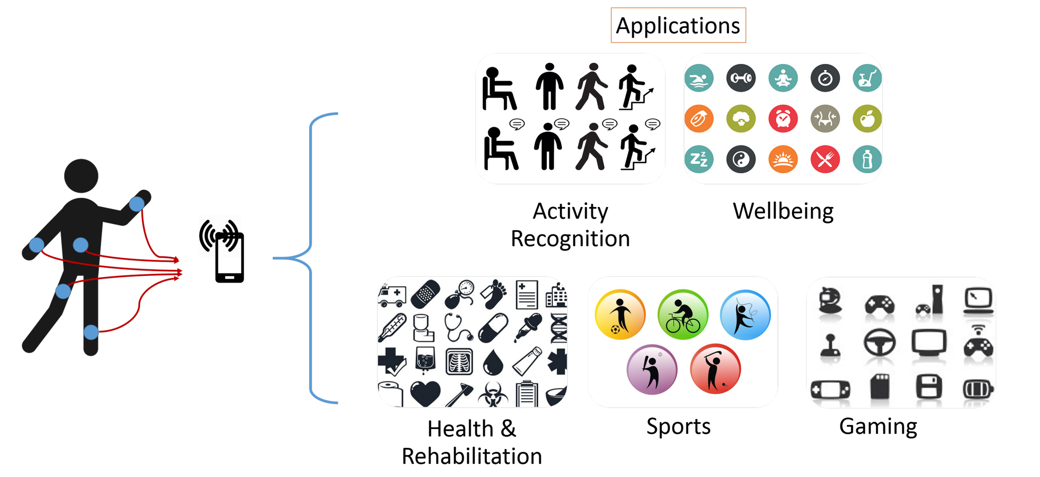
Motivation - Online Human Activity Recognition



Online Human Activity Recognition

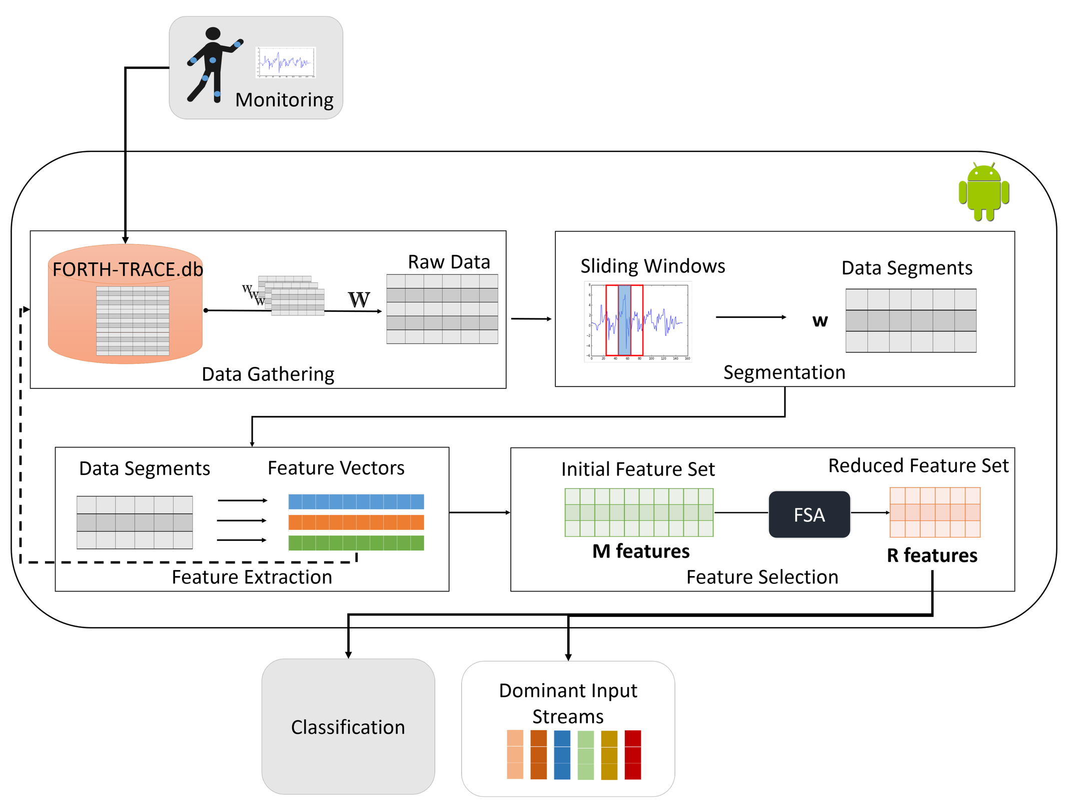
- Massive Streams of daily generated data
- Constantly alternating activities

Goals and Contribution

Feature Selection for HAR

- ✔ Reduce raw signals into discriminative features
- ✔ Accurate interpretation of Human Activities
- **Software Framework** for Online Feature Selection on Mobile Devices
- Explore online aspects of popular Feature Selection Algorithms
- Analyze FSA performance with respect to variation of activities

Proposed Online Feature Selection Architecture



Online Feature Selection library

- Extension of **FORTH-TRACE library** [1] in Android Devices
- **Dynamic data processing and storage**
  $\Rightarrow$ Database integration to load and store data
- **Dynamic data gathering**
  $\Rightarrow$ Temporal windows of size W to simulate online scenario
- **Online** Feature Extraction and Feature Selection

Experimental Setup

Dynamic Data Gathering

- FORTH-TRACE Dataset [1] (duration of activities: 18 min)
- Temporal windows $W \in \{2, 3, 4, 5\}$ (min)
- Generating $P \in \{9, 6, 5, 4\}$ partitions

FORTH-TRACE DATASET

https://github.com/spl-icsforth/FORTH_TRACE_DATASET

Segmentation

- Sliding windows of length $w = 2s$

Feature Extraction

- Statistical Features [6]

Feature Selection

- **Unsupervised**: Feature similarity for redundancy reduction - FSSA (2002) [3]
- **Ranker**: Relief-F (1997) [4]
- **Graph-Based**: Graph Clustering with Node Centrality - GCNC (2015) [5]

Post-Processing Evaluation Metrics

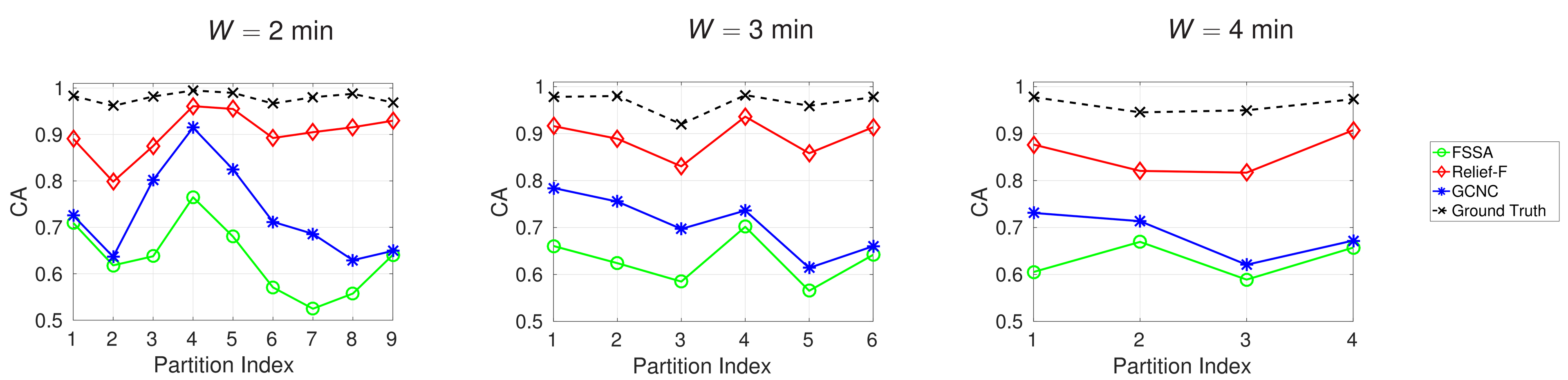
- Normalized Representation Entropy ($\bar{H}_r$) [3]
  - $\bar{H}_r \in [0, 1]$
  - Measures the amount of redundancy in feature set
- SVM classification accuracy (CA) [2]
  - Split feature set into Train (70%) and Test (30%) sets
  - Gaussian-Kernel SVM classifier

Online Performance of Library

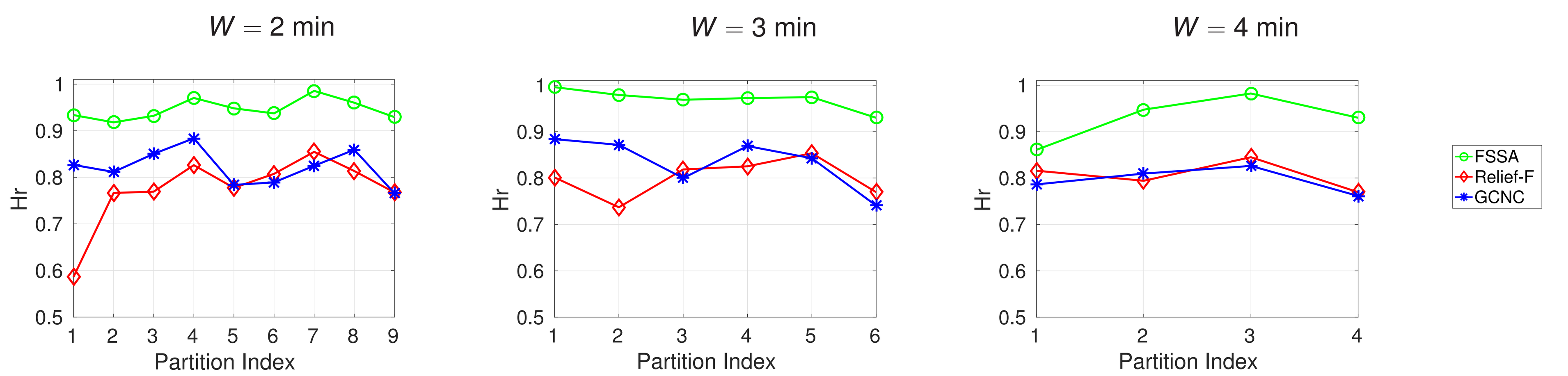
- Execution time per component
- Energy requirements of Android device

Experimental Results

Classification Accuracy w.r.t. the data chunk size W (mean values from all sensor locations)



Representation Entropy w.r.t. the data chunk size W (mean values from all sensor locations)



Inconsistent FSA performance over different temporal windows W due to variation of activity labels within different partitions P

Online HAR applications involve short data chunks!

Impact of activity labels to the Classification Accuracy

Classification Accuracy and percentage (%) of activity labels across different partitions for $W = 2$ min

Left Wrist

Partition Index	2	4	5	8
GCNC	0.66	0.81	0.84	0.68
Relief-F	0.78	0.97	0.97	0.88
FSSA	0.70	0.58	0.71	0.62

Right Thigh

Partition Index	2	4	5	8
GCNC	0.69	0.96	0.80	0.67
Relief-F	0.72	0.96	0.95	0.95
FSSA	0.62	0.84	0.74	0.54

Activity	**2**	**4**	**5**	**8**
stand	18.64	3.39	16.1	16.1
sit	41.53	-	-	-
sit & talk	26.27	-	-	-
walk	-	94.92	-	-
walk & talk	-	-	81.36	28.81
climb	-	-	-	-
climb & talk	-	-	-	50.85
postural transitions	13.56	1.69	2.54	4.23

Distribution of Activity Labels and CA

- ✔ Single primary activity $\Rightarrow$ optimal CA
- ✗ More activities $\Rightarrow$ less accurate predictions

Run-time aspects of Feature Selection library

Execution time(s) of the library components per W

W	2	3	4	5
Acquisition	1.2	1.36	1.73	1.7
Segmentation	0.73	0.95	1.14	1.16
Feature Extraction	**46.62**	**84.28**	**116.71**	**146.23**
FS: FSSA	**49.57**	**69.81**	**85.74**	**105.49**
FS: Relief-F	4.3	7.36	9.75	11.71
FS: GCNC	21.52	21.74	23.06	28.25

- **Most time consuming module:** Feature Extraction
- **FSA execution**:
- ✗ Relief-F (supervised): fast $\Rightarrow$ not suitable for online realizations
- ✔ GCNC (graph-based): adequate time and performance for integration with online architectures

Energy consumption of online library

Energy Requirement: $\sim$ 20.3 Joule

Outperforms:

- Adaptive Accelerometer Activity Recognition (A3R) algorithm [7] $\Rightarrow$ 100 Joule
- Shimmer3 Gesture Recognition application [8] $\Rightarrow$ 29.2 Joule

Reference List & Contact Details

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This work was funded by the DEDALE project, contract no. 665044, within the H2020 Framework Program of the European Commission.

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