Machine Learning Approaches to Activity Recognition and Person Identification

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Outline

- Summary
- Motivation
- Case study 1: Daily life activity recognition
- Case Study 2: Person identification
- Conclusions and future work

Summary

- Recognizing primitive daily life activities
  - 3D acceleration sensor nodes used (placed on 4 different body parts)
- Identifying persons based on footsteps
  - Floor matrix of simple binary switches used
- Statistical Machine learning
  - Discriminative kernel machines (Support Vector Machines (SVM), Gaussian Processes (GP))
  - Information fusion: combining sequential data

Motivation

- Daily life activity recognition
  - To motivate personal health care and fitness monitoring etc.
  - Small wireless wearable sensors: can be embedded in mobile devices, clothing, shoes, necklaces, watches etc.
- Person identification
  - Biometrics, personal profiling of devices and services etc.
  - Floor sensors: can be embedded to environment, transparent and natural identification
- To provide information for higher level applications (e.g., in ubiquitous systems)

Motivation (cont.)

- Statistical machine learning approaches
  - Uncertain and noisy sensor measurements
  - Non-linear dependencies between input features and output activities
  - Information fusion problems
    - Activity recognition
      - To learn to predict activities from high-dimensional input features
      - To learn to smooth and to select the most probable activity transition
    - Person identification
      - To learn to predict identity from high-dimensional input features
      - To combine the sequences of footsteps

Case study 1: Daily life activity recognition

Sensors

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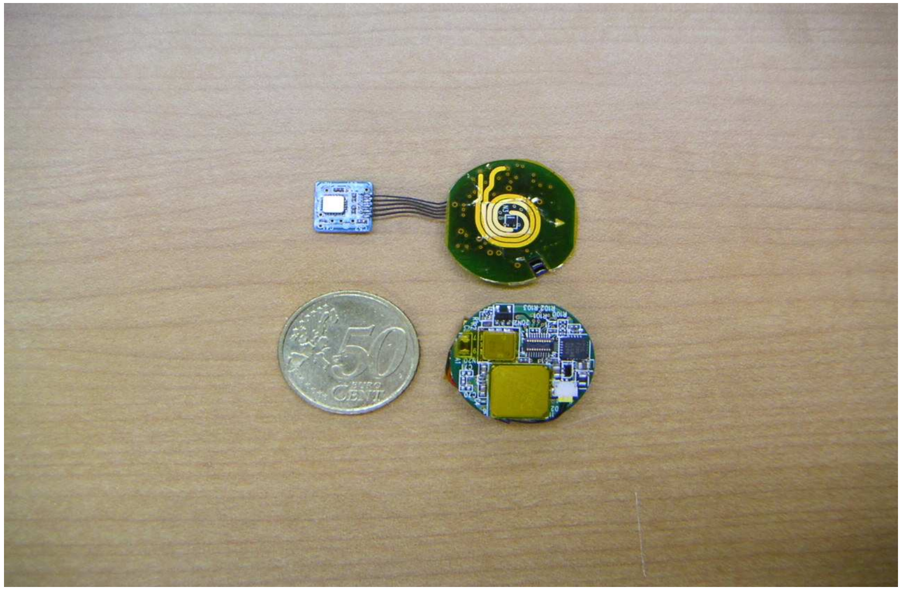

- “Cookie”
- Developed in Nokia Research Center in Tokyo (in collaboration with DCL at Waseda University)
- 3-axis acceleration data
- Range $\pm$ 3g
- Output sampling frequency 10Hz (internally 200kHz, samples are averaged and synchronized from each node)

Sensor placements

- Sensor nodes were attached to four different body parts to sense human motion and posture
  - Right thigh
  - Right wrist
  - Left wrist
  - Necklace

Activities, data collection, and features

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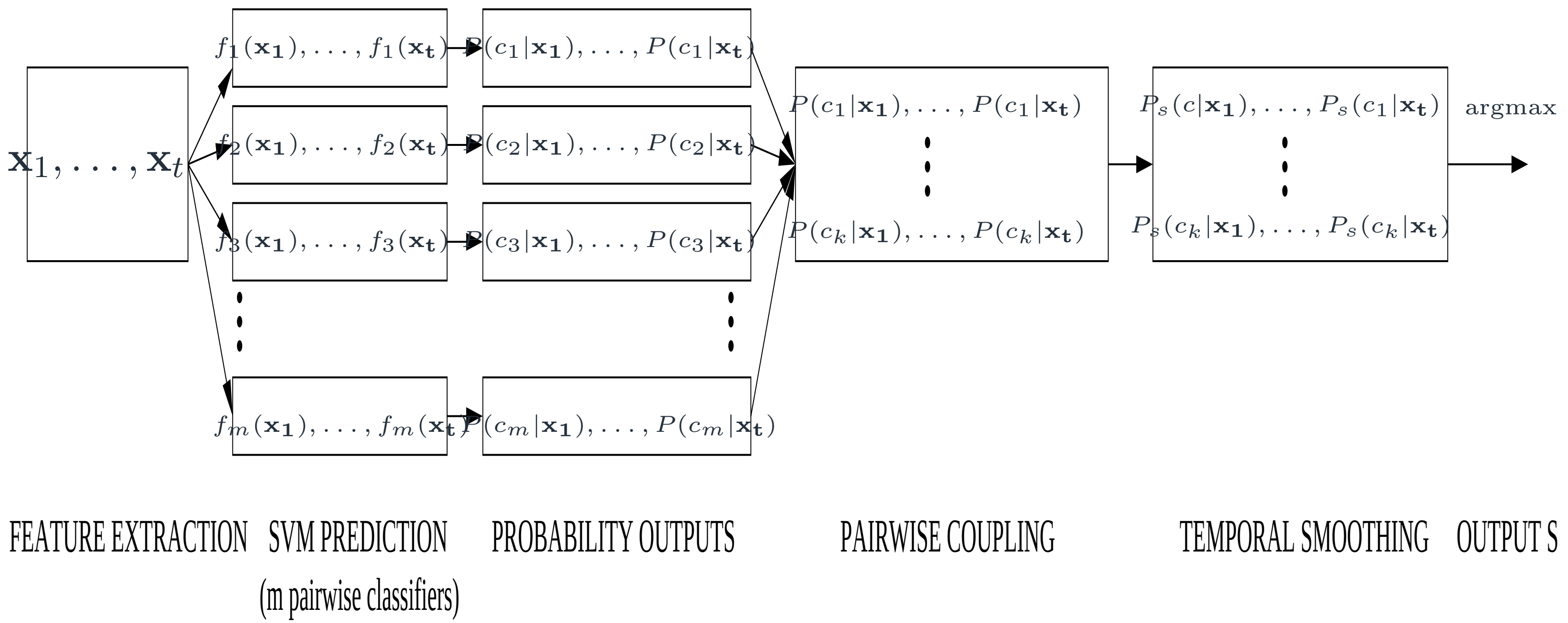
- 17 different activities were collected
  - Cleaning a whiteboard, Reading a newspaper, Standing still, Sitting and relaxing, Drinking, Brushing teeth, Sitting and watching TV, Lying down, Typing, Vacuum cleaning, Walking, Climbing stairs, Descending stairs, Riding an elevator up, Riding an elevator down, Running, Bicycling
- Semi-naturalistic labeling (i.e., annotation by subjects)
- Over 8 hours of data collected from 13 subjects
- Time domain features calculated (mean and standard deviation)

Methods

- Discriminative learning of individual activities
  - Mapping from high dimensional input feature vector to activity prediction
  - Effectively discriminates between classes (not wasting resources to model joint distributions)
  - Support Vector Machines (SVM) base classifiers
  - Only for binary classification, pairwise classifiers combined to perform multiple class classification
  - No direct posterior distribution of class labels, parametric sigmoid post-processing mapping

- Temporal smoothing for sequences
  - SVM's capability of classifying only individual examples (e.g., activities)
  - Activities are usually changing smoothly (e.g., not like walking - lying down - running)
  - Activities are rather dependent on the neighborhood labels (e.g., sitting - standing - walking - running)
  - We propose a novel algorithm which is called Discriminative Temporal Smoothing (DTS)
    - DTS uses a combination of individual posterior predictions from discriminative method (e.g., SVM) and sequential temporal information of adjacent class labels
    - On training time individual confidence measurements are collected to sequence
    - Hidden Markov Model -type transition probability matrix learning from the sequence (Forward-backward algorithm)

- A graphical presentation of sequential activity recognition



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Experimental settings

- Two different datasets are used
  - Dataset of all 17 activities
  - Combined dataset of 9 activities (some activities aggregated to more general ones)
- DTS is compared with other methods
  - SVM (no use of sequential information)
  - HMM (uses sequential information for intra-class variations)
  - SVM-HMM (combination of these two, HMM trained to SVM's outputs)

Results

- Recognition of 17 activities

	SVM	HMM	SVM-HMM	DTS
Accuracy (%)	90.65 (4.53)	84.26 (4.66)	84.39 (5.65)	**93.58 (4.15)**
Precision (%)	88.00 (4.68)	75.69 (3.04)	77.82 (5.36)	**93.88 (3.69)**
Recall (%)	87.74 (3.21)	79.74 (3.76)	81.17 (3.90)	**90.58 (3.55)**

- Recognition of 9 activities

	SVM	HMM	SVM-HMM	DTS
Accuracy (%)	94.15 (2.62)	88.75 (2.93)	90.42 (4.75)	**96.36 (2.13)**
Precision (%)	92.12 (2.98)	82.32 (4.50)	85.77 (3.14)	**96.76 (2.06)**
Recall (%)	92.10 (1.80)	86.77 (3.74)	87.89 (7.20)	**94.53 (1.05)**

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- Confusion matrix of recognizing 9 activities

%	clean	sit	stand	use stairs	brush teeth	lie down	walk	run	cycle
clean	**94.3**	1.5	1.2	0.0	0.0	0.0	2.4	0.0	0.6
sit	0.0	**99.4**	0.4	0.0	0.0	0.0	0.2	0.0	0.2
stand	3.1	2.6	**94.1**	0.0	0.2	0.0	0.0	0.0	0.0
use stairs	0.0	0.0	0.0	**70.9**	0.0	0.0	29.1	0.0	0.0
brush teeth	1.7	0.7	0.0	0.0	**97.2**	0.4	0.0	0.0	0.0
lie down	3.4	3.4	0.0	0.0	0.0	**92.7**	0.0	0.0	0.5
walk	0.0	0.0	0.0	0.2	0.0	0.0	**99.8**	0.0	0.0
run	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**100.0**	0.0
cycle	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	**99.6**

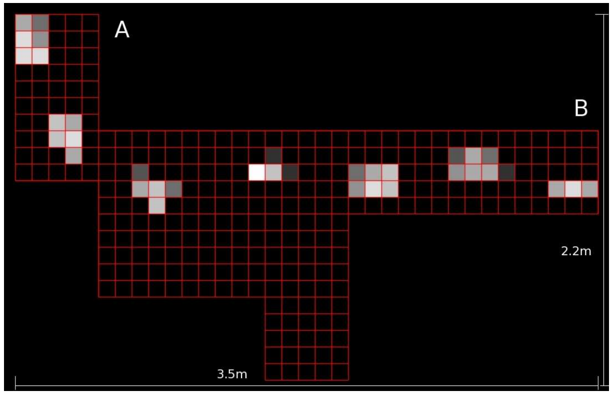
Case study 2: Person identification using simple floor sensors

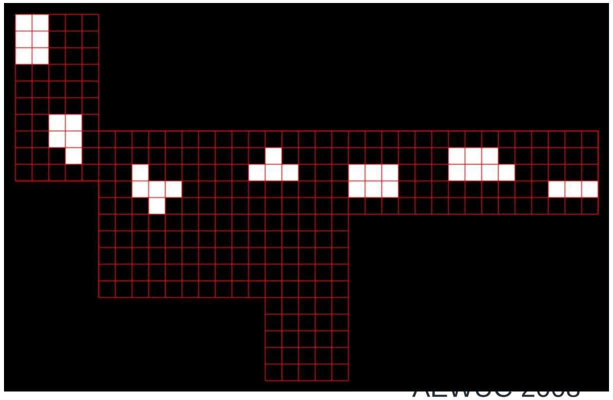
Sensors

- "InfoFloor"
- Installed in Tokyo University of Agriculture and Technology
- 10cm x 10cm binary sensor tiles
- Each unit contains 25 tiles (i.e., size of 50cm x 50 cm)
- Totally 300 binary switches
- Output sampling frequency 16Hz

Data collection and features

- Dataset collected
  - 9 persons, 20 walking sequence, ca. 150 footstep profiles / person
- Feature extraction
  - Features based on the single footstep profiles as well as walking sequence
  - When integrating data from adjacent time periods binary image can be transformed to grey-level image
  - Totally 28 features (e.g., number of activated tiles, stride length and duration)





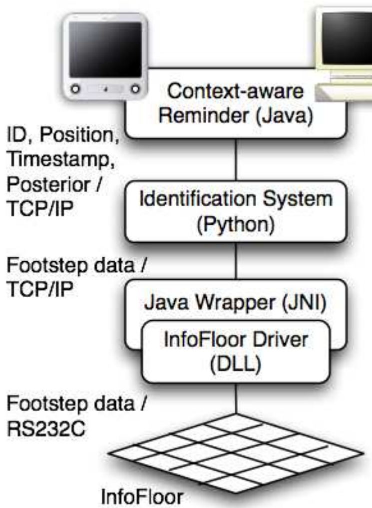
Methods

- Bayesian discriminative learning
  - Mapping from high dimensional input feature vector to person id
  - Gaussian Processes (GP) classifiers
  - Joint multiclass classification, posterior probabilities, and Bayesian model selection
- The use of sequential information from walking over the floor
  - Learning classifier from individual footstep examples (simple conventional training)
  - Combining classifier outputs (e.g., posterior probabilities)
    - Summation and product rules (easy to implement)
    - Learning the optimal combination (future work)

Identification of 9 persons

	GP (single examples)	GP (sum rule)	GP (product rule)
Accuracy (%)	64.23 (3.27)	82.33 (6.59)	84.26 (6.69)

Context-aware reminder



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Conclusions

Conclusions and future work

- We have proposed methods for activity recognition and person identification from multiple sensors
- Interesting approaches to ubiquitous and context-aware computing

- Fully optimized discriminative training for information fusion
- Combining different sensor modalities (e.g. floor and wearable nodes)
- Incremental learning (adding new activities/persons, adapt existing activities/persons)
- Semi-supervised learning (the use of non-annotated data)

- References

Suutala J., Pirttikangas S., and Röning J. (2007) **Discriminative Temporal Smoothing for Activity Recognition from Wearable Sensors**. International Symposium on Ubiquitous Computing Systems(USC2007).

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Thank You!

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