Sensor and Actuator Networks 
and the Internet of Things

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Overview

• WSANs and the Future Internet
• Smart Dust and the first generation of WSANs
• Shift to next generation WSANs and the IoT
• The Internet of People
• Analytics for IoT WSAN systems
• Capturing and employing collective behaviours
The Internet today
The Internet of Things
Device evolution


Problems and evolution

• Smart Dust faces significant problems
  – Energy harvesting
  – Maintenance
  – Programmability at the system level
• Mobility seen as significant for robustness/performance
• Popularity and proliferation of mobile networks
  – 400M sensors in mobile phones in 2014
• Shift of emphasis to smart-phone centric networks
  – e.g. sensor clouds around smart-phone core
• Shift of focus on data and human dynamics
Core ingredients

• Humans carry sensors and actuators on personal devices
• These devices interact with embedded systems such as building networks, Smart Dust, Personal Area Networks and RFID
• The IoT captures and processes the data
• Maintain, infer, characterize and provide intelligence
New problems emerge

• IoT sensor network systems generate automatically massive data sets
• How to tell what is important and what is not
• How to find significant information
• One solution we currently investigate in our group
  – To combining behaviours, preferences, or ideas of a group of people to create novel insights
  – aka collective intelligence
Significant locations

- Identify significant places
- Use mobile phone location records
- Identify hot-spots of activity
- Time specific
- Commercially available through Sense Networks
- Track real-world consumer behaviour

sensenetworks.com
RFID Analytics

- RFID-tagged products and locations
- Scan traffic at specific check points
- Analyse traffic and identify hot-spots or problem areas
- Visual tools
- Different spatial resolution

Illic et al, Auto-ID Lab Zurich

TrakSens
Social networks

• Observe social networks in the real world
• Tag and rank location of individual
• Identify meetings through collocation or device-to-device interaction
• Create social network graph
• Conduct analysis
• Reality mining data set

Shen et al, UC Davies
Patterns of behaviour

- Identify typical behaviours
- Possibly context and task specific
- Applications in navigational assistance, personalisation, recommendations
- Best-trails i.e. most popular pathways followed
  - GPS data from London Zoo
- Daily activity patterns
  - Reality Mining data

Experience Recorder

Shen et al, UC Davies
• Predict driver destination
• Use dense grid to identify locations
• Metric representations of space extremely costly
• Machine learning to identify common behaviours
• Used for navigational assistance

Krumm et al
Microsoft Research
Navigational assistance

• Find best route between two places
• Use data from an expert data set
• Taxi drivers are considered experts in this task
• Navigate like a cabbie
• Similarities of geographic navigation and web navigation

Ziebart et al, CMU

Navigationzone.net
Summarization

- Reduce a complex data set to typical behaviours
- GSM tracks over metropolitan area
- Cluster typical behaviours in profiles
- Use road graph to identify sequences
- Topological descriptions of space are more efficient

Adrienko et al
Fraunhofer IAIS
Our group’s point-of-view

• Spatiality/physicality sets most constraints, thus the starting point

• Reality is a semantic-spatiotemporal environment
  – pervasive computing technology to capture user behavior
  – identify significant landmarks and pathways
  – trail-based processing

• Core ingredients
  – trails
  – metrics of significance
  – suffix-tree based algorithms
A landmark is

• A location
  – A scanning station
  – A popular place
  – A nodal point according to Space Syntax

• A person
  – A mobile phone-carrying individual
  – A mote-tagged conference attendee

• A (physical or data) object
  – A URI
  – An RFID-tagged artefact
Identifying landmarks

• **A-priori**
  – Defined by system-specific characteristics
  – Bluetooth, WLAN, GSM etc access point
  – RFID, mote or other tag
  – Construction of space graph e.g. Space Syntax

• **A-posteriori**
  – Identify significance through use
  – e.g. Minimum Volume Embedding Algorithm
Experiments on 3 main data sets

- Dartmouth University
  - campus-wide wifi network
- Reality Mining
  - User movement over a mobile phone network
- Cityware
  - Bluetooth scanning at Bath

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Interactions</th>
<th>Users</th>
<th>Landmarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dartmouth</td>
<td>1,782,931</td>
<td>4,745</td>
<td>623</td>
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<tr>
<td>Reality Mining</td>
<td>2,536,034</td>
<td>89</td>
<td>32,628</td>
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</tbody>
</table>
Landmark analytics

- Statistics per landmark
- Total number of visits
- Visit frequency
- Average and total dwell time
- Per hour, per day, per week etc
Trail analytics

Best trails using different metrics
– frequency, time, orientation, hybrid
and constraints
– start and end at specific landmark
– passes through specific landmark
– minimum, maximum, exact trail length
– time of day, week, month etc
– nodes tagged with specific meta-data
– user-specific
Examples (1/4)

Top-10 trails by frequency
Dartmouth data set
Wi-Fi associations
3-year period
Top-3 trails by time
Exact length 3

Top-3 trails weighted
Exact length 3

Cityware data set, 3-month period
Hard to interpret visually
Nodes are individuals
Trails show patterns of contact
Top-10 trails by frequency
At least 7 different landmarks
Intel imote data set
Examples (4/4)

Concept drift: best-trail evolution over time

Reality-mining data set

Popular trails algorithm

Mobile phone (cellular and Bluetooth) over 9 months
Hit and Miss results

Using all trails in the data set.

Using best trails only.
Identify individual without ID

Reality-mining data set

Identify user 39 using 2 months for training and test on next month
Summary

• New model for WSANs
• Data capture and connectivity to the IoT
• Significant developments in recent years
• Analytics, prediction, classification