Distributed Intelligent Systems – W12:
Distributed Sensing using Sensor Networks – Power-Efficiency and Mobility
Outline

• Basic principles for energy saving in static sensor networks

• Power-efficient resource management
  – Motivation from a DIS perspective
  – Clustering and pruning
  – Temporal and spatial suppression

• Mobile sensor networks
  – Air quality monitoring
  – The OpenSense project
Problems in Distributed Sensing

Distributed solution:
- size, cost
- number
- networked
- mobile

Possible missions:
- patrolling
- searching
- mapping
- inspecting

Physical field:
- artificial or natural
- bounded or unbounded
- 2D or 3D

W12 and W13
Basic Principles for Energy-Saving Design in Static Wireless Sensor Networks
Wireless Sensor Networks

From Week 7:

– are spatially distributed systems
– exploit wireless networking as main inter-node interaction channel
– typically consist of static, resource-constrained nodes
– energy saving is a crucial driver for the design of WSN
– sensing data are typically only collected for a particular application and rarely used to control node actions: WSN are typically data-agnostic!
Generalization: Friis Laws

• Basic Friis law (open environment)

\[
\frac{P_r}{P_t} = G_t G_r \left( \frac{\lambda}{4\pi R} \right)^2
\]

- \( P_r \) = received power
- \( P_t \) = transmitted power
- \( G_t \) = gain transmitting antenna
- \( G_r \) = gain receiving antenna
- \( \lambda \) = signal wavelength
- \( R \) = distance emitter-receiver

See also W7

\[ f = \frac{c}{\lambda}! \]

• Modified Friis law (cluttered, urban environment)

\[
\frac{P_r}{P_t} = G_t G_r \left( \frac{\lambda}{4\pi} \right)^2 \left( \frac{1}{R} \right)^n
\]

- \( n \) between 2 and 5!
Communication/Computation Technology Projection

<table>
<thead>
<tr>
<th></th>
<th>1999 (Bluetooth Technology)</th>
<th>2004</th>
</tr>
</thead>
<tbody>
<tr>
<td>Communication</td>
<td>(150nJ/bit)</td>
<td>(5nJ/bit)</td>
</tr>
<tr>
<td></td>
<td>1.5mW*</td>
<td>50uW</td>
</tr>
<tr>
<td>Computation</td>
<td>~ 190 MOPS</td>
<td>(5pJ/OP)</td>
</tr>
</tbody>
</table>

Assume: 10kbit/sec. Radio, 10 m range.

Large cost of communications relative to computation continues
Communication Power Budget: Not only Transmission

• In general transceiver power consumption dominated by listening (radio on)
  – ChipCon CC2420: 19.7 mA in receiving, 17.4 mA transmitting @ 0 dBm (2.4 GHz) [W7: Mica-Z]
  – SemTech SX 1211: 3 mA in receiving, 25 mA @ +10 dBm in transmitting (900 MHz) [W7: SensorScope]

• Synchronization is key
• Low power listening protocols are key for saving power
Efficient Monitoring in Sensor Networks
WSN and DIS - Motivation

A few key questions:
– Can additional in-node/in-network intelligence help in saving energy?
– Does it make sense to have WSN data-aware (as opposed to the general data-agnostic paradigm)?
– Is there a way to make a stronger overlap between WSN and DIS?
Motivation

Minimize energy resources used – Maximize field accuracy obtained

- sample as little as possible
- communicate as little as possible

- in space
- in time

- # of messages
- comm. radius
Opportunities for Spatiotemporal Suppression in Environmental Data

- Ambient temperature
- Surface temperature
- Relative humidity

Correlation coefficient

Temperature (°C)

Distance (km)

Time (days)
Clustering and Threshold-Based Pruning
Case study: Estimating an Acoustic Field

- $4^n$ sensing cells
- $4^n$ sensor nodes
- 1 static sound source

**Performance metric:**
1. MSE (data quality)
2. A (number active nodes)

**Objective function:**
$f_{obj}(\text{MSE, A})$
Hierarchical Topology – Quadtree

Network level

- Multiple roles → layers
- Hierarchy:
  - Bottom-up measurements
  - Top-down control
Hierarchical Topology – Quadtree

Single node level

- Messaging protocol dependant on:
  - sender-ID
  - sender-layer

Communication channels

- Channels given by quadtree
Each node is assigned a specific $L_{k_{\text{max}}}$ by architectural design.

- **Layer increment:** if all child nodes processed
- **Idle node:** if pruned by clusterhead
- **Data:** clusterhead replaces pruned children
An Intuitive Illustration

Naïve Sampling

Threshold-based Sampling

(a)  

(b)  

(c)  

(d)
From a Centralized Formula to Distributed Control

\[
\hat{f}_n = \arg\min_{f(\theta), \theta \in \Theta_n} R(f(\theta), x) + 2s^2 p(n)|\theta|
\]

Centralized formulation [1]
\(s\): signal noise (homogeneous)
\(p\): monot. increasing function of \(n\)
\(|\theta|\): number of active nodes in cluster

Distributed control?

Experimental Setup

The e-puck robot:
- Trinaural microphone array (28.8 Hz)
- Short range communication
  - subset of 802.15.4 Zigbee
  - comm. range: 10cm - 5m

Setup:
- 1.5m x 1.5m arena
- 16 e-puck nodes (static sensor stations)
- 1 static sound source (white noise, const. intensity)
Experimental Results

Number of active nodes

MSE

Setup:
• 10 runs, variable source placements / threshold
• 12 thresholds, with $s$ in [0..12'000]
• Model with $t_x = 0.3$
Spatiotemporal Suppression of Data Reporting
Saving Communication
Energy via Efficient Reporting

Temporal suppression
  • Has my value changed recently?

Spatial suppression
  • Are my neighbors reporting similar measurements?
Temporal Suppression

Ex: Barebones temporal suppression (field change in gray)
Temporal Suppression

Ex: Barebones temporal suppression (reporting node in red)
Temporal Suppression

Ex: Barebones temporal suppression
Temporal Suppression

Ex: Barebones temporal suppression
Efficient Monitoring

Monitor edge constraints instead of individual nodes
Efficient Monitoring

Monitor edge constraints instead of individual nodes
Efficient Monitoring

Monitor edge constraints instead of individual nodes
Efficient Monitoring

Monitor edge constraints instead of individual nodes
Constraint Chaining

• Suppression-based algorithm: Constraint Chaining (Conch) [1]
• Monitor edge constraints instead of sensor values
  • Historical data to identify performant edges

Conch
Conch

$v_{new} \neq v_{old}$

Updater
Conch

\[ v_{new} \neq v_{old} \]
Conch

$\Delta_{new} = v_{new} - v_{recv}$
Conch

\[ d_{\text{new}} = v_{\text{new}} - v_{\text{recv}} \]

\[ d_{\text{old}} \neq d_{\text{new}} \]
Conch
Conch

Use historical data to construct a Minimal Spanning Tree (MST)
Conch

Use historical data to construct an MST

\[ \text{freq}(d_{ij}) \times \text{dist}(e_{ij}) \]
Conch

"Conch plan"
Testbed
In-Network Power Monitoring

Sensors:
- Battery voltage
- Solar voltage
- Incoming solar current
- Datalogger current
- Power board current
- Sensor chain current
Results with Basic CONCH

• Four weeks on the outdoor testbed
• Limited adaptivity to network changes
  • Replanning costs $O(|E|) + GPRS$
• Unstable network led to most nodes reporting directly to the sink
• 45% of messages suppressed while algorithm was functional
Results with Advanced CONCH

• Autoregressive model for more compressed comparison of differences:
  • AR-Conch: 57% suppression rate

• Autoregressive model + in-network distributed implementation for enhanced adaptive behavior
  • AR-DConch: 64% suppression rate
Concrete Energy Savings

Not significant since:

- Radio on for several seconds (overhearing)
- Transmission takes 6 ms max
- Two minutes idle at ~11.8mW

Energy savings given fixed 50% suppression rate (calibrated simulation in TOSSIM)

Our settings
Mobile Sensor Networks - The OpenSense Project
Problems in Distributed Sensing

Current solution:
- sparse sensing
- expensive
- field estimation via models
- possible mobility

Possible missions:
- patrolling
- searching
- mapping
- inspecting

Physical field:
- artificial or natural
- bounded or unbounded
- 2D or 3D

Distributed solution for augmentation:
- size, cost
- number
- networked
- mobile
Importance of Air Quality

On March 25, 2014, the WHO reported:

“... in 2012 around 7 million people died – one in eight of total deaths – as a result air pollution exposure. This finding more than doubles previous estimates and confirms that air pollution is now the **world’s largest single environmental health risk.**”

“The new estimates are not only based on more knowledge about the diseases caused by air pollution, but also upon better assessment of human exposure to air pollutants **through the use of improved measurements and technology.**”

Urban Air Pollution

Air pollution in urban areas is a global concern
  • affects quality of life and health
  • urban population is increasing

Air pollution is highly location-dependent
  • traffic chokepoints
  • urban canyons
  • industrial installations

Air pollution is time-dependent
  • rush hours
  • weather
  • industrial activities
Objectives in Air Pollution Monitoring

Accurate location-dependent and real-time information on air pollution is needed

Officials
- public health studies
- environmental engineers: location of pollution sources
- municipalities: creating incentives to reduce environmental footprint

Citizens
- advice for outside activities
- assessment of long-term exposure
- pollution maps

OpenSense ultra fine particle levels map in Zürich during winter months
Satellite-based remote sensing

Examples:
• Measurements of Pollution in the Troposphere (MOPITT on Terra satellite)
• Ozone Measurement Instrument (OMI on Aura satellite)

Features:
• daily scans
• large coverage
• homogeneous quality
• sensitive to cloud coverage
• low resolution
Monitoring Today

Stationary and expensive stations

Sparse sensor network (Nabel)

Expensive mobile high fidelity equipment

Coarse models (mesoscale = 1km²)

Personal exposure with specialized punctual studies

- Garage
- Vehicle
- Road
- Indoor
Value of Dense Measurements

- Traditional approach
  - Few stations
  - Low resolution interpolated estimates of pollutant concentrations across massive regions

- Recent results
  - Massive deployment of stations (150) at street-level (2008/2009 New York City Community Air Quality Survey)
  - Pollutants of interest heavily concentrated along roads with high traffic densities
OpenSense
(2011-2013)

Karl Aberer (PI), EPFL
Co-PIs:
Alcherio Martinoli, Boi Faltings, Martin Vetterli, EPFL
Lothar Thiele, ETH Zürich

http://opensense.epfl.ch
http://www.nano-tera.ch/projects/401.php
OpenSense II
(2013-2016)

PI: Alcherio Martinoli, EPFL
Co-PIs: Karl Aberer, Boi Faltings, EPFL
Andreas Krause, Lothar Thiele, ETH Zürich
Lukas Emmenegger, EMPA
Murielle Bochud, University Hospital Lausanne
Michael Riediker, Institute for Work and Health, Lausanne

http://opensense.epfl.ch
http://www.nano-tera.ch/projects/423.php
Research Challenges

**SENSING SYSTEM**
From many wireless, mobile, heterogeneous, unreliable raw measurements...

**INFORMATION SYSTEM**
...to reliable, understandable and Web-accessible real-time information

1. Sensing system
2. Data acquisition and modeling
3. Community involvement

Air pollution as exemplary use case for other environmental phenomena:
Radiation, noise, energy

Microscale: 5m^2
OpenSense System Vision

Measurement data
Crowdsensors, mobile sensors, monitoring stations

Land-use and weather
Terrain, meteorology, emission sources, population

Exposure information
Personal recommendations, health studies, city mobility planning, crowdsensing methods

High-resolution pollution maps
Physics-based and data-driven modeling methods
## Deployments and Approaches

<table>
<thead>
<tr>
<th>Deployments</th>
<th>Lausanne</th>
<th>Zurich</th>
</tr>
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<tbody>
<tr>
<td>Mapping Approach</td>
<td><a href="#">EPFL</a></td>
<td><a href="#">ETH Zürich</a></td>
</tr>
<tr>
<td>Data-driven Physics-based</td>
<td><a href="#">EMPA</a></td>
<td><a href="#">EMPA</a></td>
</tr>
</tbody>
</table>
High-Resolution Maps:
Enhanced Physics-Based Modeling Techniques
Enhanced Physics-Based Modeling

Measurement data
High-end monitoring stations

Land-use and weather
Terrain, meteorology, emission sources, population

Exposure information
Personal recommendations, health studies, city mobility planning

High-resolution pollution maps
Physics-based modeling methods
The GRAMM/GRAL Modeling Framework

Observations
- wind speed
- wind direction
- stability

10 years of hourly concentration maps
- Traffic
- Heating
- Industry

Temporal profiles
- Traffic
- Heating
- Industry

GRAMM/GRAL (meso/CFD) catalogue of wind fields

GRAL catalogue of concentration fields

[Berchet et al., Atmospheric Environment, 2017]
Multi-year Simulations of NO\(_x\) and PM10

- 5 m resolution, hourly output, 0-30 m above ground level
- Lausanne: ten years, 10 emission categories
- Evaluation with in situ measurements:
  - Bias < 25%
  - Correlation > 0.7 for hourly concentrations
  - Correlation > 0.8 for daily averages

Lausanne, annual mean NO\(_x\)

Comparison with NABEL NO\(_x\) measurements in Lausanne
Physics-Based Modeling

**Strengths:**
- Well-established, can be extended with a chemistry module
- Cost-effective (only standard IT infrastructure on top of existing measurement stations)
- Natively designed for 3D field estimation

**Weaknesses:**
- Estimations instead of measurements
- Dependency on the existence and accuracy of an emission catalog
- Cannot capture real-time field changes due to peculiar events (e.g., emergency situations, special event in the city, traffic re-routing)
High-Resolution Maps: Dense Measurements Augmented with Statistical Modeling Techniques
Data-Driven Modeling

**Measurement data**
Crowdsensors, mobile sensors, monitoring stations

**Land-use and weather**
Terrain, meteorology, emission sources, population

**Exposure information**
Personal recommendations, health studies, city mobility planning, crowdsensing methods

**High-resolution pollution maps**
Data-driven modeling methods
OpenSense Sensing Platform (Lausanne Deployment)

- Mission: measure gas-phase pollutants (CO, NO₂, O₃, CO₂), particulate matter (PM), temperature and humidity

- Gases:
  - mix of small, relatively low cost, electrochemical, metal oxide, and optical sensors.
  - slow response time; need re-calibration; cross-sensitive (low selectivity)

- Particles:
  - physical metrics: Lung-Deposited Surface Area (LDSA)
  - nanoscale sensitivity (<100 nanometers)
  - high cost

- Mobility and energy: leverage public transportation vehicles!
Enable high spatio-temporal resolution monitoring of urban air quality through mobile wireless sensor networks.

- Modular & flexible
- Using low-cost sensors

- Slow sensor response
- Mitigation approaches

- Novel model-based & mobility-aware approaches

- Novel statistical techniques
- Heterogeneous data sources

[Arfie, PhD thesis, 2016]
System Design → Mobility Effects → Calibration → Mapping

**Contributors:** Adrian Arfire, Emmanuel Droz, Alexander Bahr, Julien Eberle (LSIR-EPFL), Ali Marjovi, Christophe Paccolat
Sensor Node Design

- Data logging & Communication
- Localization
- Air Sampling
  - Gas Sampler
  - PM Sampler

CAN Bus
Air Sampling

Naneos Partector
nanoparticle detector

City Technology A3CO
CO sensor

Vehicle anchor

Protective mask

GE Telaire 6613
CO2 sensor

SGX Sensortech MiCS-OZ 47
O3 sensor

KWJ Engineering SNL-NO2
NO2 sensor
Localization

Based on u-blox LEA-6R module (GPS + DR)

Additional features:
- 3-axis accelerometer
- Vehicle context data
The Sensor Network

In the field

10 Lausanne buses
Static deployment at NABEL site for calibration & testing
Electric vehicle node for targeted research

Server-side

Diagram showing the server-side setup with connections to mobile WSN (wireless sensor network) and back-end server for replication, leading to front-end server for end-users.
System Performance

Spatio-temporal variability
System Performance

Coverage

Hourly

Daily

Weekly

Monthly

Coverage probability of the network
System Performance

Data throughput

Deployment start: October 22, 2013 (~ 3 years), numerical values on Sep 28, 2016

<table>
<thead>
<tr>
<th>Measurement</th>
<th>Sampling rate</th>
<th># of measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>LDSA (PM)</td>
<td>1 s</td>
<td>&gt; 203 million</td>
</tr>
<tr>
<td>[CO, NO₂, CO₂]</td>
<td>5 s</td>
<td>&gt; 101 million</td>
</tr>
<tr>
<td>[O₃, temp., RH]</td>
<td>5 s</td>
<td>&gt; 71 million</td>
</tr>
<tr>
<td>GPS fix</td>
<td>1 s</td>
<td>&gt; 325 million</td>
</tr>
<tr>
<td>[odometer, accelerometer]</td>
<td>0.25 s</td>
<td>&gt; 1352 million</td>
</tr>
<tr>
<td>vehicle context info</td>
<td>event-driven</td>
<td>&gt; 14 million</td>
</tr>
</tbody>
</table>

• [Arfire et al., in preparation]
Contributors: Adrian Arfire, Ali Marjovi
Mobility Effect

- Except for work in robot olfaction, largely unaddressed

Strategies:
- Limiting robot velocity
- Cycling between movement & stationary measurement
- Customized air sampling systems
Experimental Set-up

- Traversing system
- Sensor module
- Smoke plume
- Wind direction

miniPID
Signal Reconstruction through Deconvolution

\[ s(t) \rightarrow h(t) \rightarrow r(t) + \epsilon(t) \rightarrow g(t) \rightarrow \hat{s}(t) \]

- **s(t)**: True signal
- **h(t)**: Sensor model
- **r(t)**: Noise
- **\( \epsilon(t) \)**: Noise
- **g(t)**: Deconvolution filter
- **\( \hat{s}(t) \)**: Estimated signal

Graph showing comparison of reference, measured, and deconvolved signals over position in meters.
Signal Reconstruction through Deconvolution

Results

• Consistent performance improvement

• Reduction of RMSE drops as the speed increases (SNR decreases)
Active Sampling System Design

**Actuation:** axial fans, diaphragm pumps
Air Sampling System Comparison

Results

- Best performance: **pump-based sniffers**
Outdoor Experimental Validation

[Arfie et al., AIM 2016, EWSN 2016]
System Design → Mobility Effects → Calibration → Mapping

Contributors: Adrian Arfire, Ali Marjovi, Nicolas Bigler
Model-based Rendezvous Calibration

Sensor model selection

\[ m_1: s(t) = p_0 + p_1 \cdot y(t) \]
\[ m_2: s(t) = p_0 + p_1 \cdot y(t) + \frac{p_2}{t} \]
\[ m_3: s(t) = p_0 + p_1 \cdot y(t) + \frac{p_2}{t} + \frac{p_3}{T(t)} \]
\[ m_4: s(t) = p_0 + (p_1 + \frac{p_2}{t}) \cdot y(t) + p_3 \cdot t + \frac{p_4}{T(t)} \]
\[ m_5: s(t) = p_0 + p_1 \cdot y(t) + \frac{p_2}{p_3 + t} + \frac{p_4}{T(t)} \]
\[ m_6: s(t) = p_0 + (p_1 + \frac{p_2}{T(t)}) \cdot y(t) + \frac{p_3}{p_4 + t} + p_5 \cdot T(t) \]

where:
- \( s(t) \) – sensor reading
- \( y(t) \) – true CO value
- \( T(t) \) – temperature
Mobility-aware Rendezvous Calibration

1. Calibration set
2. Get parameters
3. Fit sensor model

- $s_i$
- $s_j$
- $G(\omega)$

enough data
Mobility-aware Rendezvous Calibration

Results

Calibration results for the sensor node deployed on bus 602

[Arfire et al., IEEE SENSORS 2016]
System Design → Mobility Effects → Calibration → Mapping

**Contributors:** Ali Marjovi, Adrian Arfire, Loïc Frund, Fabrizzio Gonzales, Thomas Coral, Jonathan Giezendanner
Mapping Problem

- LDSA data is sparse
- Coverage of sensors is incomplete and dynamic

- Generating complete maps is a challenge.

Solution:
- Other sources of data is required
- Models are required to estimate the LDSA in locations/times of interest
Statistical Modeling - Overview

- Measurement Data
- Explanatory Variables
  - Spatio-temporal aggregation
  - Proxy pollutants, weather, traffic, land-use, etc.
  - Modeling method
  - Linear regression, ANN, Gaussian Process regression, PGM, etc.
- Air pollution map
Explanatory Variables

Proxy-pollutant data (NABEL)

Meteorological data (MeteoSwiss)

Land-use data (Swisstopo & GEOSTAT)

Traffic count data (Transitec)
Modeling Methods

**Basic Log-Linear (BLL) regression**
\[
\log(L_{m}) = \alpha_0 + \sum_{i=1}^{9} \alpha_i \cdot \log(v_i)
\]

**Network-based Log-Linear (NLL) regression**
- Dependency network – measurement correlation & complementarity
\[
\log(L_{S_m}) = \alpha_0 + \sum_{i=1}^{9} \alpha_i \cdot \log(v_i) + \sum_{[m-n] \in E} \alpha_n \cdot \log(L_{S_n})
\]

**Basic Log-Linear with Land-Use (BLL-LU) regression**
\[
\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{l=1}^{17} \gamma_l \cdot \log(U_{l,S_m})
\]

**Land-Use Network-based Log-Linear (LU-NLL) regression**
- Dependency network – land-use data
\[
\log(L_{S_m}) = \alpha + \sum_{i=1}^{9} \beta_i \cdot \log(v_i) + \sum_{l=1}^{17} \gamma_l \cdot \log(U_{l,S_m}) + \sum_{[m-n] \in E} \delta_n \cdot \log(L_{S_n})
\]

**Deep Learning Model (DLM)**
- ANN training technique

---
Performance

Results

<table>
<thead>
<tr>
<th>Local models (BLL, NLL)</th>
<th>Global models (BLL-LU, LU-NLL, DLM)</th>
</tr>
</thead>
</table>

RMSE (µm²/cm³)

- Daily
- Weekly
- Monthly
- Quarterly

[Marjovi et al., DCOSS 15]
[Marjovi et al., EWSN 17]
Pollution Map Example

Coverage extended to the regions where both land-use and traffic data is available.
Higher Resolution Maps

- Not using traffic data
Conclusion
Take Home Messages

- Environmental data are (usually) highly redundant
- Embedded intelligence at the node/network level has the potential to remove that redundancy and save energy
- AI techniques have been studied in simulation but they are difficult to bring to real systems
- Design for dynamic environments is difficult because both dynamic environmental processes and dynamic network conditions must be considered
- Network stack may limit potential gains in energy saving of the intelligent algorithm; it is often a question of robustness versus efficiency
Take Home Messages

• Mobility in sensor networks offers wider coverage with the same number of nodes and can bring advantages in deployment, gathering, and maintenance operations

• Depending on the sensing modality and technology, mobile nodes can bring additional challenges that eventually results in additional complexity at the node level

• Increasing the resolution of air pollution data is necessary for understanding health impact

• Data quality is critical in these type of applications, so appropriate techniques for handling drifting, low selectivity, and mobility impact on low-cost sensors are key

• The OpenSense project gathered probably the largest dataset on urban air quality in the world and pioneered the use of public transportation for mobile sensor networks


