Wireless Sensor Networks for Distributed Chemical Sensing: Addressing Power Consumption Limits With On-Board Intelligence

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The Problem

- Single point chemical measurement
  - Propagation inefficient
- Distributed sensing is solution
  - Limited by power management strategies

Authors' Contributions

- Implementation of power savings sensor censoring strategies
- Target: cooperative chemical sensing with TinyOS
- On-board sensor fusion unit
- Nodes capable of deciding informative content from sensed data

Authors' Motives

- Capability to detect and monitor for chemicals is a potentially life saving asset.
- e.g., plume of H_2 spill is unpredictable, probability of single sensor being hit is negligible.
  1. Detectors can follow random paths
     - Then try to detect source by using chemical spill search algorithms
  2. Rely on fixed low-cost distributed sensors
     - Cooperate to reconstruct chemical image

The Distributed Approach

- Flexible, Scalable, enhanced SNR, robust and self-healing
- When sensor fails, network can est. response based on previous behavior
  - Via reconstructing routing trees
- Every sensing node has computing abilities
  - Stability improved through drift correction

Optimal Sensors

- Low power capability
- Low cost
- Long-time stability, reliability
- Easy to integrate with simple signal conditioning schemes

- ^ An ideal non-existent device

Considering Sensor Candidates

- Metal Oxide (MOX) Chemical Sensors
  - Requires high working temps
  - Average power consumption is in 200-800mW range (too power hungry!)
- Polymer-based chemiresistor, resonators and mass sensors (QMBs, SAWs)
  - Operated at room temps
  - Not as common as MOXs
  - Low power consumption = Huge advantage
  - Not efficient at low concentrations
  - Negatively affected by humidity

Considering Sensor Candidates

- LED/Polymer-based Optical Sensors
  - Suitable where high limits of detection not issue
  - Low cost, reliable, low power req.
  - Suitable sensitivity requires laser source, increases cost and power req.

State of the Art

- Current "e-nose" not designed to tackle distributed sensing problem
- MOX sensors tested in WSN for indoor gas detection
- Heating procedure* modified to increase battery life, sample range 2-min
    - Up to a year
    - Increased response time

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* Bicelli, Sebastian, et al. "Model and experimental characterization of the dynamic behavior of low-power carbon monoxide MOX sensors operated with pulsed temperature profiles." *Instrumentation and Measurement, IEEE Transactions on* 58.5 (2009): 1324-1332.

Equipment/Strategy Used

- TinyOS, TelosB-like motes
- Four room-temperature operating low-power polymeric chemical sensors
  - Extend entire sensory network lifespan
- On-board intelligence implemented, only informative packets transmitted
- Goals: monitor indoor air quality, detect toxic/dangerous VOC spills.

Modules Sensors Array

	Polymer Chemical	**Structure**
Sensor 1	Poly-(methylmethacrylate) (PMMA)	$[CH_2C(CH_3)(CO_2CH_3)]n$
Sensor 2	Poly-(2hydroxyethylmetacrylate) (PHEMA)	$H(NHCH_2CH_2)nNH_2$
Sensor 3	Poly-(styrene) (PS)	$(C_6H_{10}O_3)n$
Sensor 4	Poly-(ethylenimine) linear (PEI)	$[CH_2CH(C_6H_5)]n$

- 4 polymer-carbon black nanocomposite sensors
- Suitable: low-power, rapid switch
  - Mechanism based on “swelling”

Swelling

- When polymer film exposed to certain vapor, swells while absorbing small amt of polymer
- Disrupts conductive filler pathways, pushing particles apart, electric resistance increases
- Because room temp, low power consumption
- If properly conditioned, stable
- Poor selectivity and sensitivity

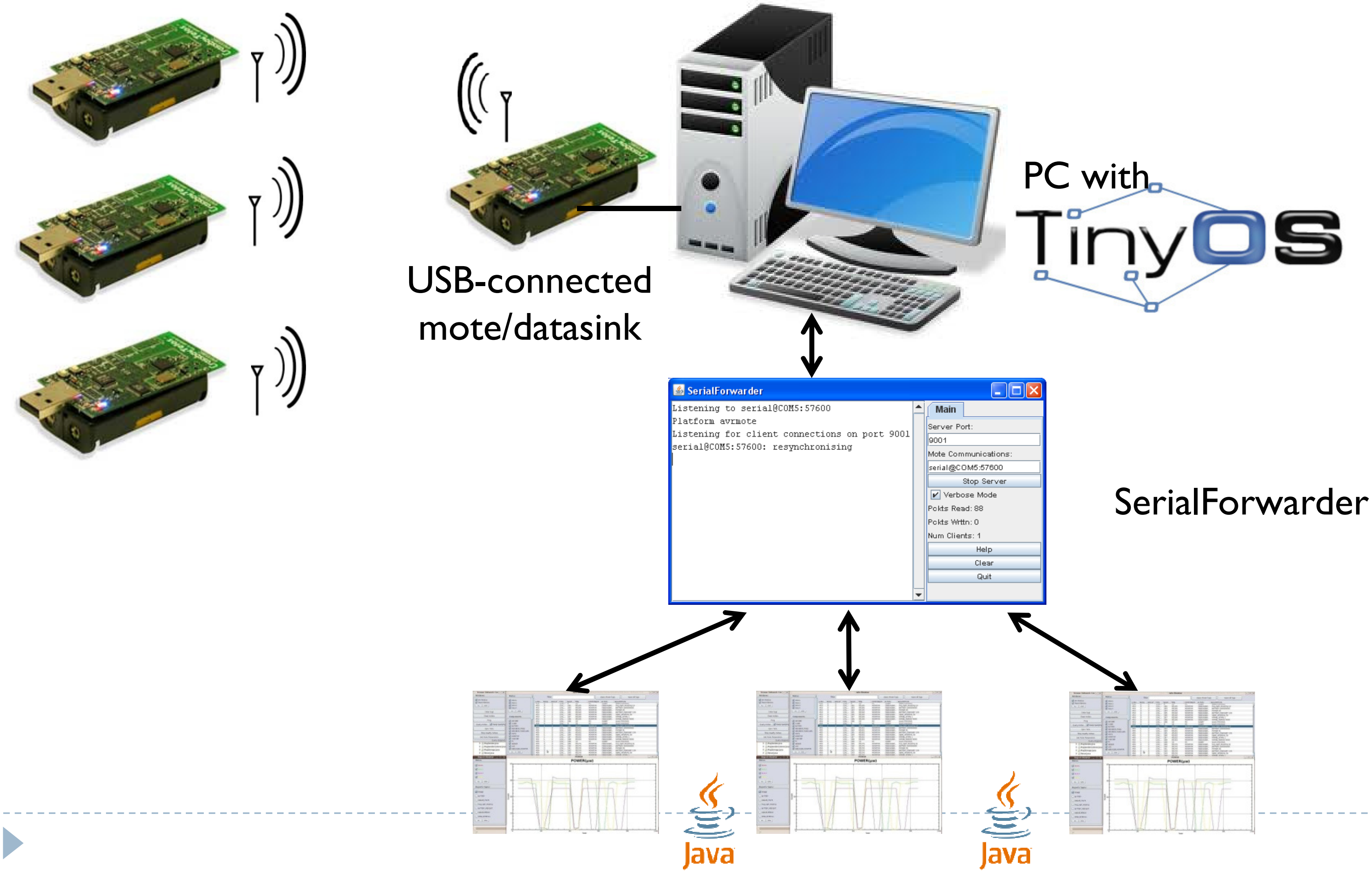
Core Mote

- TelosB, AA powered, MSP430F1611 µController
- 1.8V with a quick wake-up low-power mode
- SHT11 humidity and temp sensor
- Chosen because of low-power sleep, quick recovery and community support

Embedded Software

- Domain-specific optimization led to choice of TinyOS as runtime support and OS
- Power management module allows auto-management of active, idle, sleep state
- C-derivative NesC provides module-based TinyOS interface
  - Only essential modules for runtime written to binary

Experimental Setup



USB-connected mote/datasink

PC with TinyOS

SerialForwarder

```
Listening to serial@COM5:57600
Platform avrmote
Listening for client connections on port 9001
serial@COM5:57600: resynchronising
```

Server Port: 9001

Mote Communications: serial@COM5:57600

☑ Verbose Mode

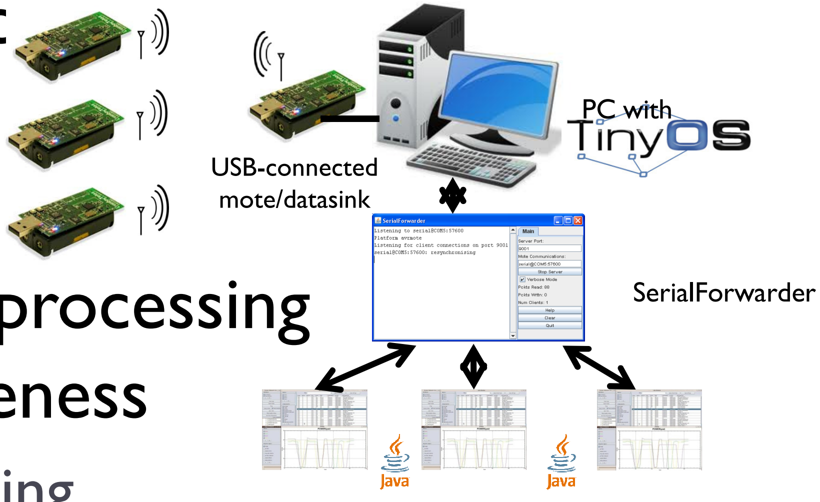
Pckts Read: 88

Pckts Wrttn: 0

Num Clients: 1

Experimental Setup

- Hosts 2 possible pattern rec & sensor fusion sub-sys



1. Connect sensor raw data processing component, local sit. awareness
   - Est. pollutant concentration using trained neural network algorithm
2. Provide sensor fusion services
   - To reconstruct olfactory image where deployed
   - “Under design” by authors

Mote Duty Cycles

1. **Sleep** – MCU and radio turned to standby
2. **Sensing** – data acquisition and ADC conversion
3. **Computing** – acquired data prep'd for transmission
4. **Transmission/Reception** – data transfer to sink

Low-Power Listening

- LPL algorithm requires radio only to be switched on just long enough to detect carrier on channel

```
 if(carrierDetected)
    routePacketToDataSink()

//after timeout
sleep()
```

Results

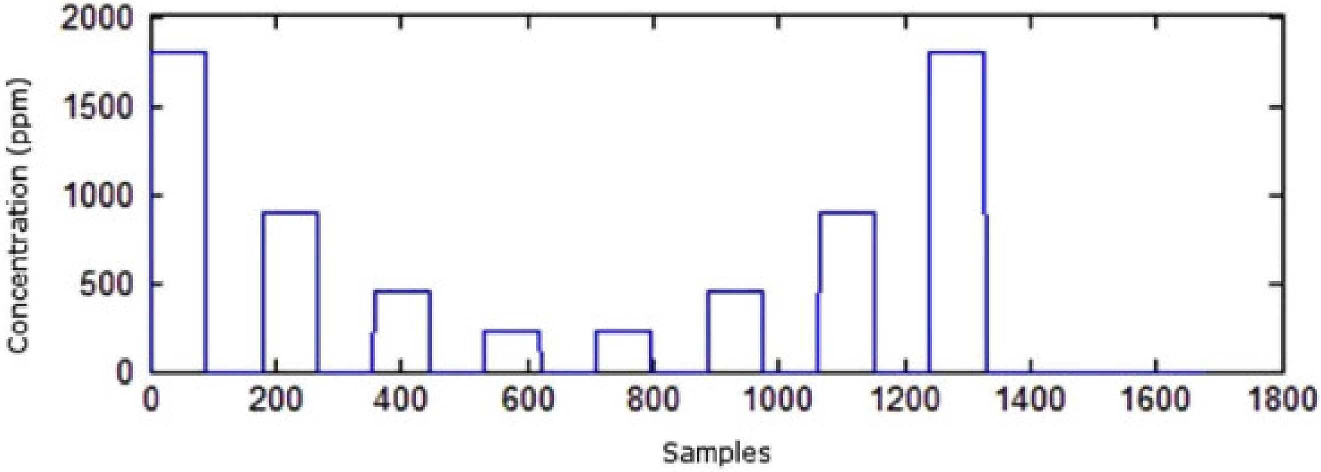
- Again, the goal:
    - Present sensor censoring power management strategies based on sensor fusion component for long-term operation
- Prior to transmission, determine if info is useful to transmit and do so if so

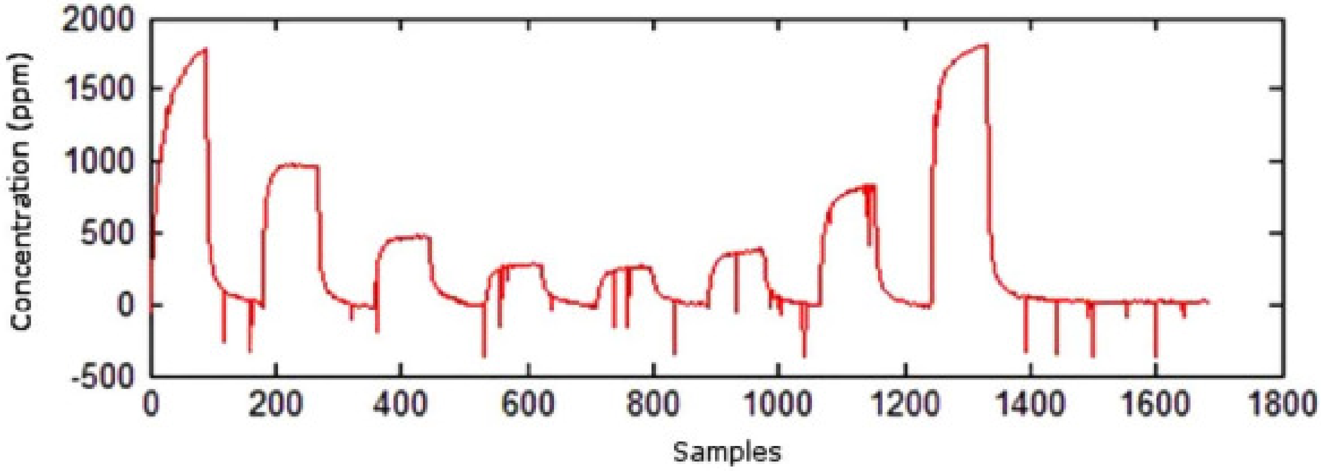
Configuration Readings

- Sleeping Mode
  - *f* = 1Hz
  - Sensor stays in sleeping mode
  - I = 12 μA drawn
- Wakeup Period
  - I=5 mA mean current draw
- Data capture and conversion
  - I=19 mA
  - Radio is main source of power consumption

Acetic Acid Concentration

ESTIMATION | TRUE CONCENTRATION





Module Lifespan

- Est'd using $I_{cc,mean}$ considers battery capability, conversion efficiency, power supply voltage gain
- Est'd over multiple phases of duty cycle

$$I_{cc,\,mean} = \frac{T_{RS}}{T} I_{RS} + \frac{T_{RW}}{T} I_{RW} + \frac{T_{A}}{T} I_{A} + \frac{T_{A}}{T} I_{T}$$

Calculated Mean Lifespan

$$I_{cc,\,mean} = \frac{T_{RS}}{T} I_{RS} + \frac{T_{RW}}{T} I_{RW} + \frac{T_A}{T} I_A + \frac{T_A}{T} I_T$$

Operating phase	**Time [ms]**	**Current request [mA]**
Radio Sleep (RS)	$T_{RS}=888$	$I_{RS}=0.012$
Radio Wakeup (RW)	$T_{RW}=7$	$I_{RW}=5$
Acquisition (A)	$T_A=37$	$I_A=19$
Computing (C)	$T_C=25$	$I_C=2.5$
Transmission (T)	$T_T=68$	$I_T=18$

Battery Life Estimation

- Function of battery capacity (C = 3500 mAh)
- …and total current draw
  - Sum of $I_{b,mean}$=(30/1000*38)=1.14mA
  - …and $I_{CC,mean}$=1.97mA

$$BL = \frac{C}{I_{CC,\, mean} + I_{b,\, mean}}$$

- Tested At 1Hz for 47 days

Further Experimental Setup

- Ad hoc lab-scale experiment
- To save battery energy, single mote should be able to decide whether to Xmit sampled data on basis of concentration of two gases
  - Acetic Acid
  - Ethanol
- Concentrations
  - [225,450,900,1800] ppm for Acetic Acid
  - [200,500,1000,2000] ppm for Ethanol
- Controlled Humidity 30%
- 3 layered feedforward neural network (FFNN) dev'd

The Feedforward neural network (FFNN)

- Implm'd in NesC, limited memory footprint
- 4 input neurons, 10 hidden layer neurons, 2 output neurons
- Outputs indicate concentration of simulated pollutants
- Trained in MATLAB to reach real-time estimation solving classification & regression problem

FFNN Training

- Normally steady-state response used
  - Remaining samples used as validation
- Expect sign error in transient samples
- Est error avg'd on all samples →transient cause big hit on synthetic performance indic.
- Validation by Mean Abs Error (MAE) over analyte concentration range span
  - 6% (10% std.dev) for Acetic Acid
  - 11% (11% std. dev) for Ethanol

The Real Objective

- Sensor censorship strategy transmission vs. processing tradeoff by sensor fusion component complexity
- Memory footprint assessed

Algorithm	**Bytes in ROM**	**Bytes in RAM**
Basic	20380	574
Basic + Neural Network comp'nt	27340	910

Neural Network Cost

- Additional 2.5mA over 25ms time span (includes function call overhead)
- Reassessing total power consumption:
- Using a Bernoulli R.V. $X \sim B(1, p)$

$$I_{CC,mean}^{NN} = I_{RS}\left(1 - \frac{T_{RW} + T_A + T_T + T_C}{T}\right) + I_{RW}\frac{T_{RW}}{T} + I_A\frac{T_A}{T} + I_T\frac{T_T}{T} + I_C\frac{T_C}{T}$$

Neural Network Cost

$$I_{CC,mean}^{NN} = I_{RS}\left(1 - \frac{T_{RS}^{'}p + T_{RS}^{''}(1-p)}{T}\right) + I_{RW}\frac{T_{RW}}{T}p$$

$$+ I_{A}^{''}\frac{T_{A}}{T}(1-p) + I_{A}^{'}\frac{T_{A}}{T}p + I_{T}\frac{T_{T}}{T}p + I_{C}\frac{TC}{T}$$

where

$$\begin{cases} T_{RS}^{'} = T - T_{RW} - T_{A} - T_{T} - T_{C} \\ T_{RS}^{''} = T - T_{A} - T_{C} \end{cases}$$

- Worst case is obtained when p=1, all samples refer to signif. Events
- Equating above and sans NN addition with p as independent var, p=0.97

What does p=0.97 mean?

- The percentage threshold under which NN-based sensor censoring becomes more efficient with regard to power management
- In industrial chemical spills, even with false positives, expect p<100 signif. samples/day

Conclusion

- With trained nodes, sensor censoring strategies can be used to optimize the lifespan by preventing unnecessary transmission and retaining low latency

References

- De Vito, Saverio, et al. "Wireless sensor networks for distributed chemical sensing: Addressing power consumption limits with on-board intelligence." *Sensors Journal, IEEE* 11.4 (2011): 947-955.
- Levis, Philip, et al. "Tinyos: An operating system for sensor networks." *Ambient intelligence* 35 (2005).
- Bicelli, Sebastian, et al. "Model and experimental characterization of the dynamic behavior of low-power carbon monoxide MOX sensors operated with pulsed temperature profiles." *Instrumentation and Measurement, IEEE Transactions on* 58.5 (2009): 1324-1332.