Agenzia nazionale per le nuove tecnologie, l'energia e lo sviluppo economico sostenibile

EUROPEAN COOPERATION IN SCIENCE AND TECHNOLOGY

2012

Invited Contribution:

WIRELESS CHEMICAL SENSORS NETWORKS FOR AIR QUALITY MONITORING

CHALLENGES AND OPPORTUNITIES

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NORIMBERGA, 23/04/2012

OUTLINE:

- WIRELESS CHEMICAL SENSING (WHAT & WHY)
- COMMON FRAMEWORK & CHALLENGES
- MODULE CALIBRATION (AND DRIFT COUNTERACTION)
- THE POWER BOTTLENECK
- SENSOR FUSION
- CONCLUSIONS

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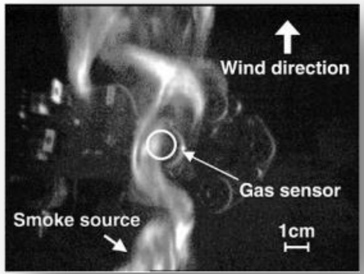
DISTRIBUTED CHEMICAL SENSING (WHAT & WHY)

Out of the Lab, in open air (3D) settings, the problem of Chemicals identification and quantification is strongly affected by propagation characteristics of chemical signal propagation.

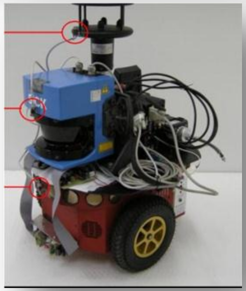
- Diffusion (sometimes negligible)
- Air flows
- Turbulence (in indoor and outdoor settings)
- Canyon effects (in city scapes)



… often make the use of a single point of measurement inefficient.

Two different approaches in literature:

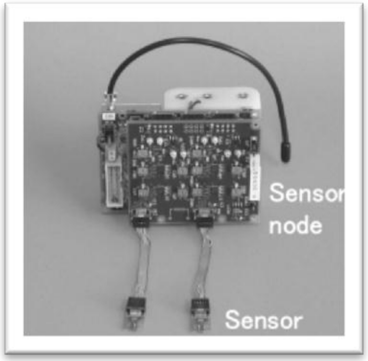
a) A single, moving agent, equipped with a chemical sensors array



b) A pervasive network of chemical sensors arrays

Why Wireless?

Wireless chemical sensing platforms are an ideal architecture for achieving real world distributed chemical qualitative and quantitative analysis capability in several real world apps:



+ Easy to deploy & Operate
+ Robust to Node Failures
+ Allows Pervasive Knowledge
+ Rapid Detection of Plumes

In turn, Single moving agent is:

- More effective in source declaration
- Easier to maintain

In theory,they can be mixed with a flock of moving agents

WCSN Primary applications:

Indoor/outdoor pollution Monitoring:

•Indoor Air Quality

•Energy Efficiency of HVAC systems

•City pollution monitoring

Safety & Security:

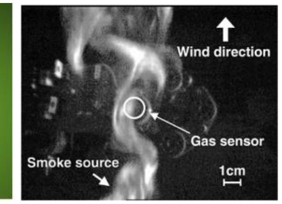
Gas spills Detection

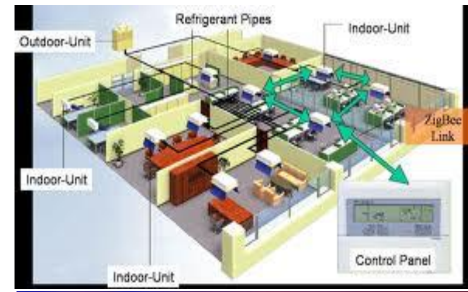
Flammable gas Detection

Geochemical monitoring (Volcanic fumaroles)

Explosives Detection

Drug factories localization



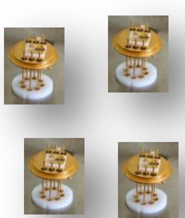


A COMMON FRAMEWORK:

Ideally, We aim to build:

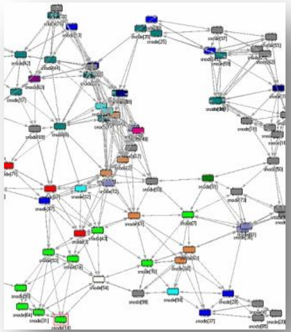
Compact-Intelligent-Cooperating-Easy-to-Deploy

chemical sensing platforms capable to act as a network to reconstruct a 3D Chemical image for the sensed environment

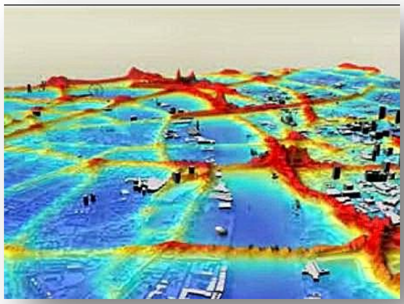


Sense…

Calibrate…



Cooperate…



[© King's College London]

Semantic Value

A COMMON FRAMEWORK - > COMMON CHALLENGES

In this common framework, a small number of important issues seems to recurrently arise:

- We need Low Cost sensors, Low cost platforms to deal with numerosity
- Effective Module Calibration -> (In Lab?, On Field?,Drifts?)
- Calibration Transfer -> (How to deal with sensors diversity)
- Energy Efficiency -> (Operation on Batteries)
- Sensor Fusion -> (How to reach situational awareness)

SINGLE MODULE CALIBRATION
HOW TO TRAIN YOUR PLATFORM TO OPERATE ON FIELD

The Goal: **Calibration of a wireless (3G) 5 MOX based PV powered multisensor system for densifying air pollution monitoring network in cities.**

- **Single analytes Calibration ?**

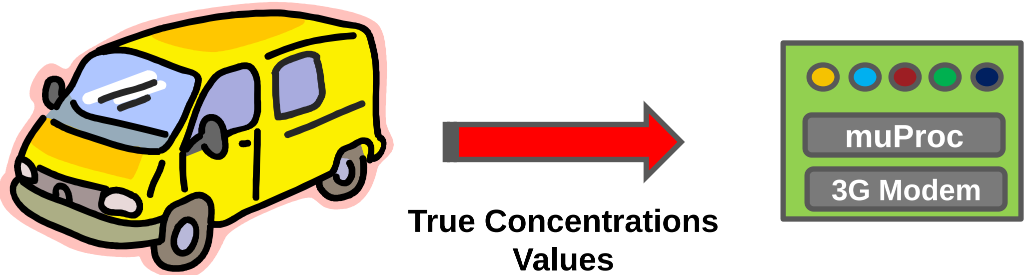
Interference set in! When mixed, gases affect the response of all sensors in your array.

- **Synthetic Mixtures ?**

You have no means to cope with the number of possible, unforeseeable interferents

The Idea: **On Field Calibration**

Use of a mobile spectrometers-based station to produce the GT for the statistical Multivariate calibration (ANN, SVR) of the multisensor system responses.

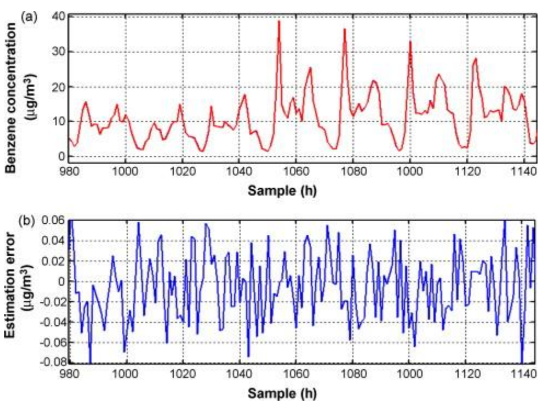


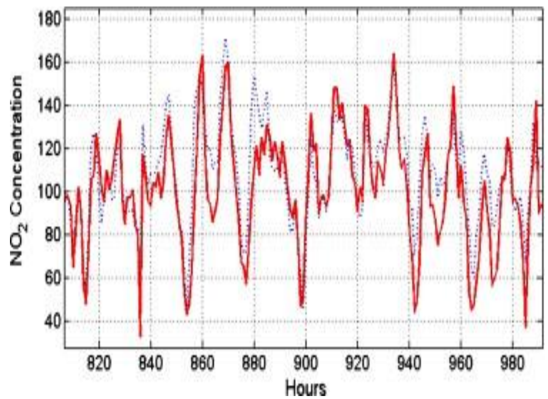
S. De Vito et al.; Sensors & Actuators,B Vol. 129, 1, Feb. 2008

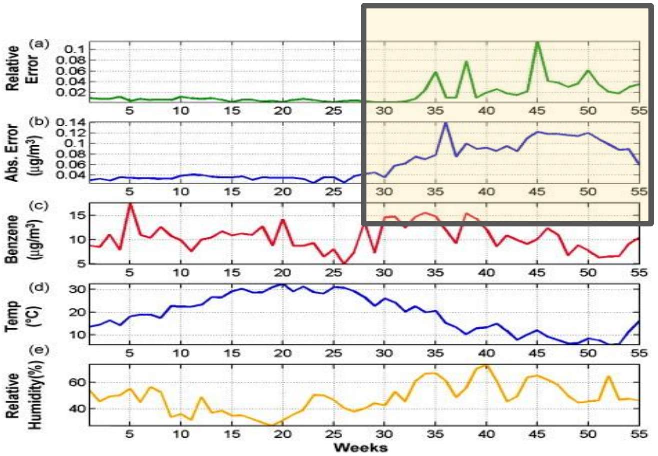
SINGLE MODULE CALIBRATION:
HOW TO TRAIN YOUR PLATFORM TO OPERATE ON FIELD

Outcome:

- ANN also learns to exploit correlations among multiple sensors [Strength but also weakness]
- Good results, very low relative error on the concentration estimation of Benzene and CO
- Acceptable results for the concentration estimation of NOx
- NO2 performance needs definitely to be improved







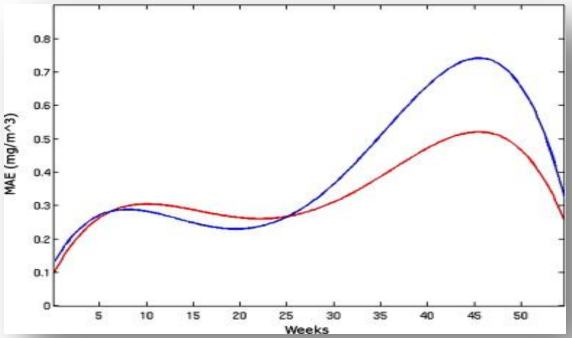
Big Issues:

- # of needed training samples (ten days) was too big to calibrate tenth or hundreds of multisensor devices
- Sensors and Concept Drift problems become significant after 4-6 Months

You cannot think of moving your mobile station from device to device again to (re)calibrate.

S. De Vito et al.; Sensors & Actuators,B Vol. 143, 1, Dec. 2009

DRIFT COUNTERACTION (& DATASET REDUCTION)



- Sensors Drift is a well known problem for solid state based devices…
- Concept drift, often neglected, is the sensor response variation due to target variables pdf and environmental settings variation (RH, Humidity, changes in absolute and relative concentration of chemicals and their interferents, etc.)

Drift is often tackled with **recalibrations** or sensor response **correction** approaches with very interesting results.

Both these approaches require a valuable resource: **Time (Samples)!**

- Time to calibrate the drift correction approach
- Time to recalibrate (when on field you need a GT generator!)

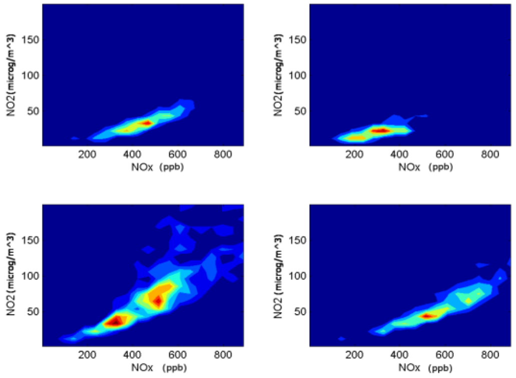
The Idea: Exploit **Semisupervised learning approaches** for sensors and concept drift effects reduction

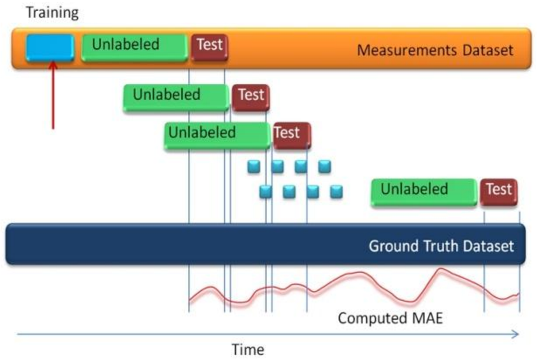
DRIFT Counteraction (& Training Dataset reduction)

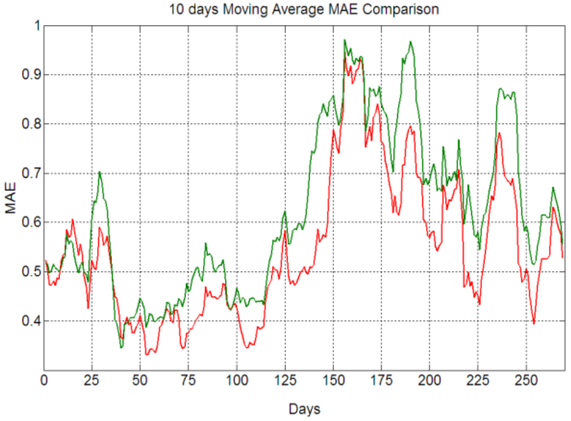
Semi supervised learning, based on manifold and cluster hypothesis, aims to exploit both

- supervised training samples (for achieving a limited but well fond knowledgeof the problem)
- Unsupervised training samples to **adapt** and complete the (limited) knowledge the system has gained before

Our group applied this technique to the drift effect reduction in the previous setting obtaining encouraging results by using a very limited number of supervised calibration points (24Hrs).



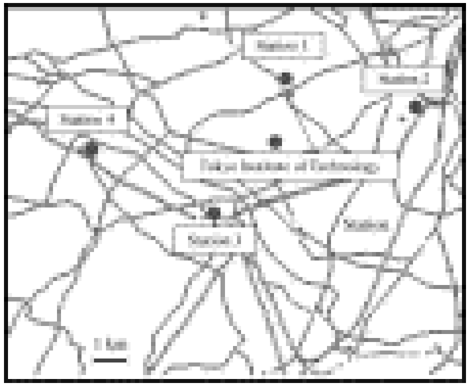




S. De Vito et al.; Accepted fo publication in IEEE Sensors 2012

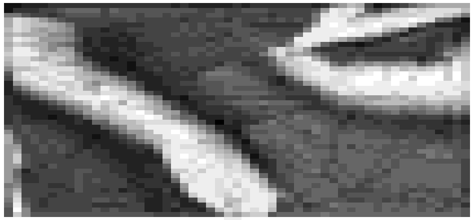
MUTUAL (RE)CALIBRATION

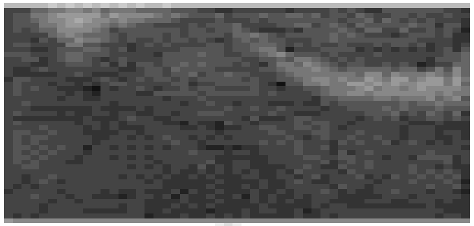
Multiple devices could, in theory, cross re-calibrate theirselves in order to counter the sensors drift effects:

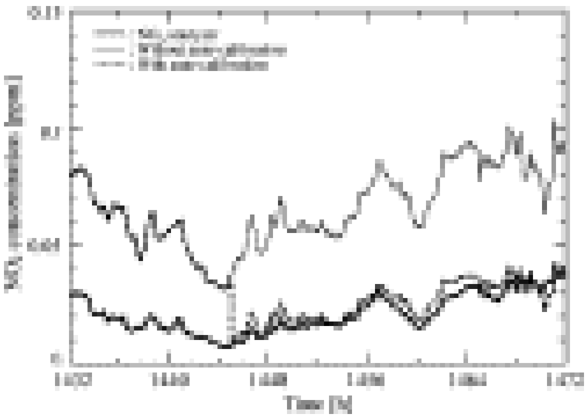


When very low pollution levels are detected together with some favourable meteo conditions (T,RH,Wind speed) than baseline response is re-calibrated.

The procedure helped to reduce sensor drift effects.

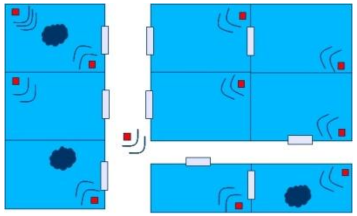






Tsujita et al. Gas sensor network for air-pollution monitoring, Sens & Act. B, 110, 2, 2005

THE POWER BOTTLENECK (d-IAQ scenario)



The development of WCSN is currently hampered by technological limits on solid state sensors power management.

e.g: Most commercially MOX sensors consumes up to 400mW in their operating phase, their use is totally prevented in battery operated e-noses

Solutions:

a) Develop (RT/LT) operating sensors with good sensitivity and low LOD
b) Operate MOX with extremely low power Temp management cycles **(Flammini et al,2007)**

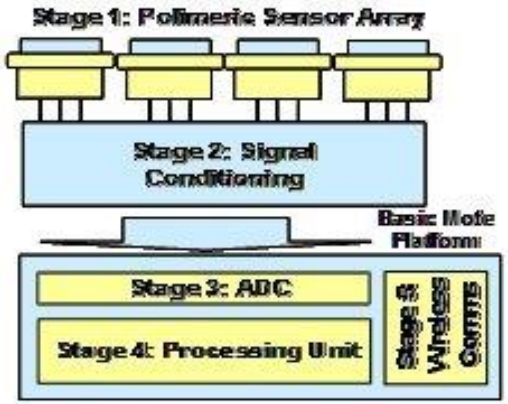
However, even when goal is reached, transmission power needs limit the operative life of continuously sampling motes (safety or security critical applications).

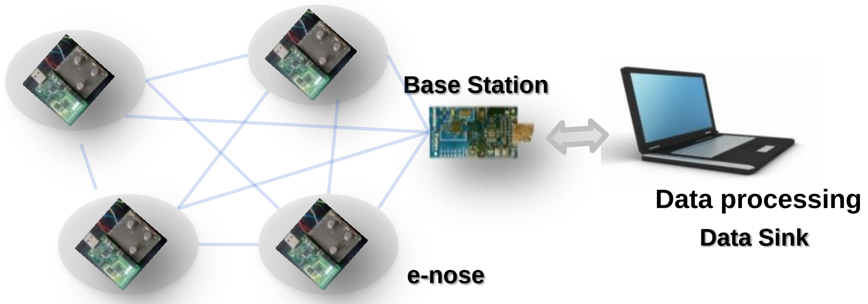
Sensor censoring strategies have to be developed in order to solve this issue.

Censoring = Eliminate uninformative data transmission

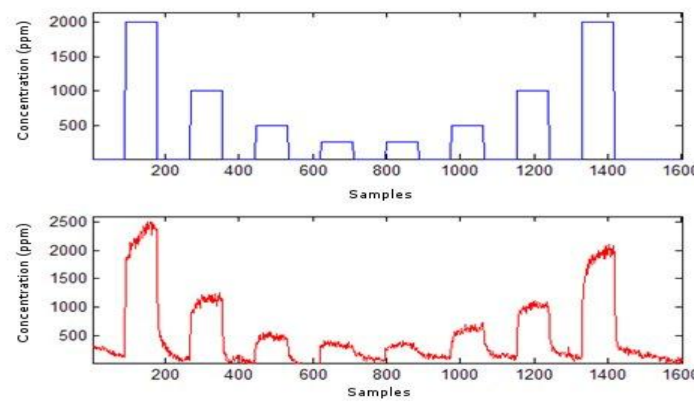
Use of low power sensors: RT Operating Polymer/CB Arrays

TinyNose (patent pending)





...TinyNose in a nutshell...	
No. of sensors	up to 4 (chemiresistors)
Sensitive materials	polymer nanocomposites
Sensor operating temperature	Room Temperature
Additional Sensors	Temperature, Humidity, Light (PAR,TSR)
Power Supply	Two AA Batteries
Battery lifetime	Up to two years @ 15 sec Sampling period
Components operating system and Data acquisition	TinyOS, Easy data access trough TCP/IP rebroadcaster, Java GUI
Wireless Comm. standard	IEEE 802.15.4 with mesh capability [2.4 GHz ISM Band)
Comm range	Up to 50 meters indoor, 250 meters outdoor
Suitable for:	Distributed Chemical sensing, Smart Environments, Security.

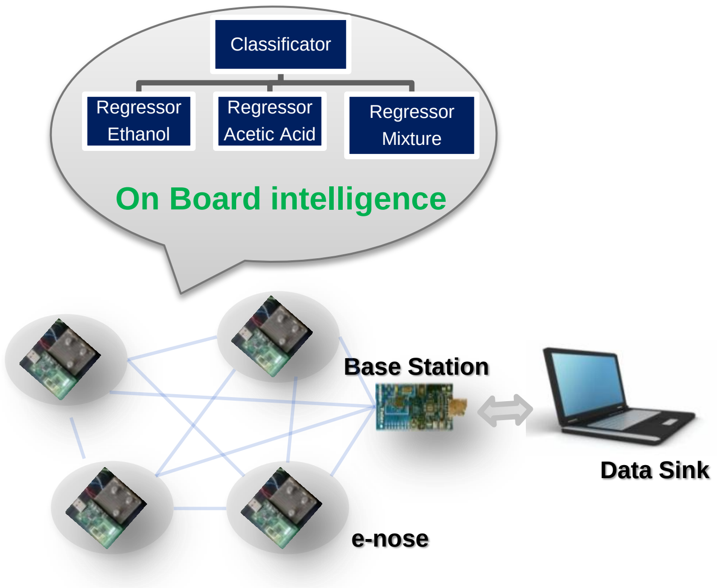


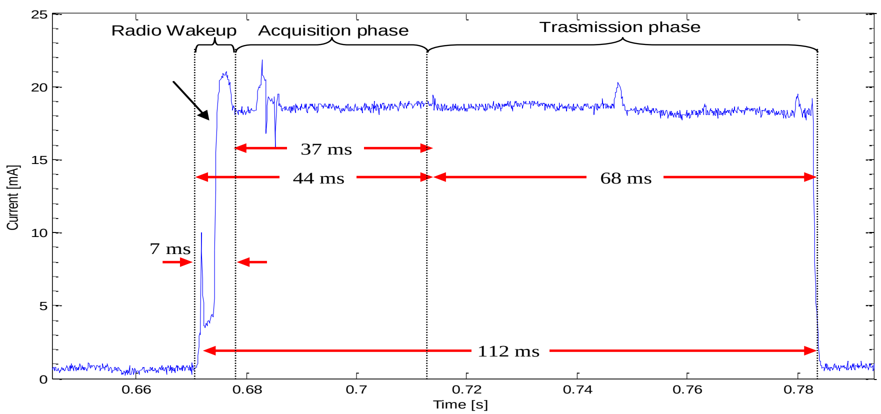
S. De Vito et al. IEEE Sensors Conference, 2008

Apart from high LOD and instabilities, we wanted to focus on unuseful information transfer….

On Board Intelligence for Sensor Censoring

The problem: Recognize uninformative data acquisitions (low concentrations of relevant pollutant or dangerous gas) in presence of interferents in a continuous monitoring scenario





Experimental Setting:

•Two mock Pollutants (Acetic Acid, Ethanol)
•In lab calibration of TinyNose equipped with
•On-Board ANN sw component (NesC).
•Threshold level for Ethanol = 100ppm (/2000ppm)
•p=0.01 probability of positive event

Results:

•Computational footprint tradeoff (2.5mAx25ms)
•1% False Positive rate
•Extension of lifetime from 47days (1Hz sample f) to 113 days

S. De Vito et al. IEEE Sensors Journal, Apr. 2011

SENSOR FUSION

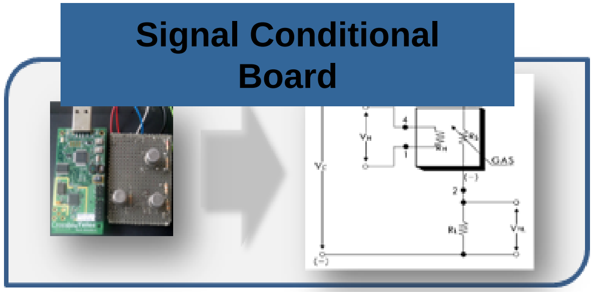
The amount of data produced can be confusing, you have to extract the semantic content you want form the continuous data stream:

a) Concentration of pollutants on a 2D citymap for urban planning purposes
b) Location of a (moving) source of flammable gases or a spill
c) 3D reconstruction of air quality for energy efficient HVAC control in smart cities

The architecture

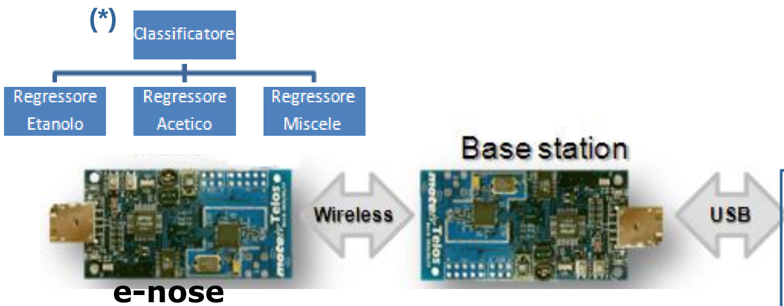
Each sensor array (4(+2) MOX sensors) has been assembled on a signal conditioning board, connected to a commercial WSN platform (*Crossbow TelosB mote*) and integrated in a compact plastic case

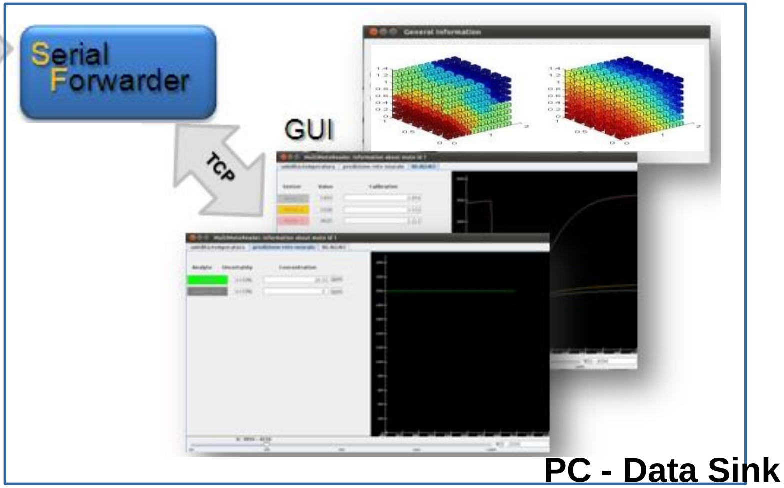
Software components on-board network motes, ad hoc designed and developed, ensure data acquisition, local processing and transmission capabilities



***TelosB* mote is a TinyOS compliant platform equipped with:**

- ***TI-MSP4300 low power µcontroller***
- ***CC2420 Zigbee capable radio***
- ***Hamamatsu digital T/RH sensors***
- ***several A/D and D/A as well as digital I/O lines for sensors and peripheral connections***





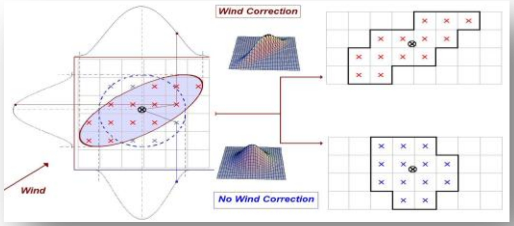
At the data sink, a java based component performs data logging and rebroadcasting features towards remote monitoring GUIs while ad hoc developed software components provides the sensor fusion capabilities

(*) Powered by: TinyOS e NesC

SENSOR FUSION

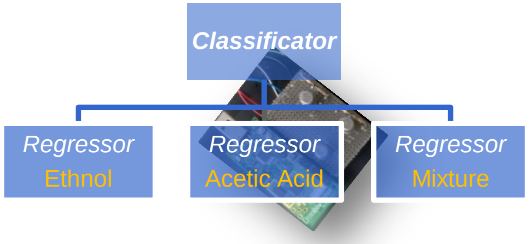
Indoor 3D Reconstruction with Kernel-DM Algorithm (Reggente et al., 2010)
Originally developed for moving robotic agents, reconstruct the 3D distribution by weigthting local readings with 3D RBF. Can cope with air flows.

$$r^{(k)} = \alpha^{(k)} * \frac{R^{(k)}}{\Omega^{(k)}} + \left\{1 - \alpha^{(k)}\right\} * r_0$$

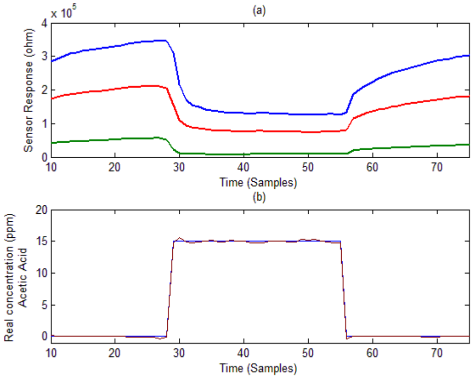


We derived a WCSN formulation for intelligent w-noses. in wich:

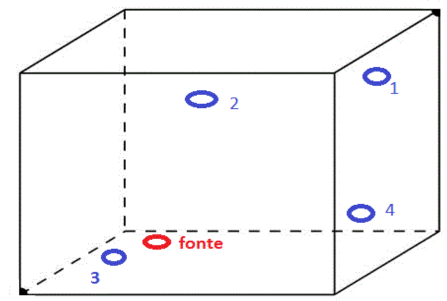
Every node should be capable of local estimations



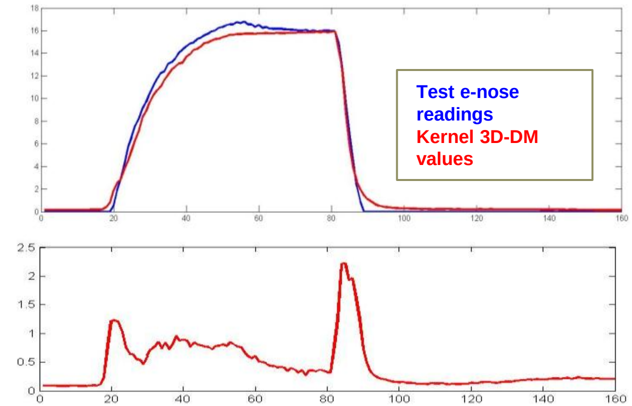
The RBF parameters can be tuned with an unsupervised mutual cross-validation approach that can be iterated



Each w-nose was calibrated (in lab) towards the target analytes (in mixture). An ANN component was embedded.

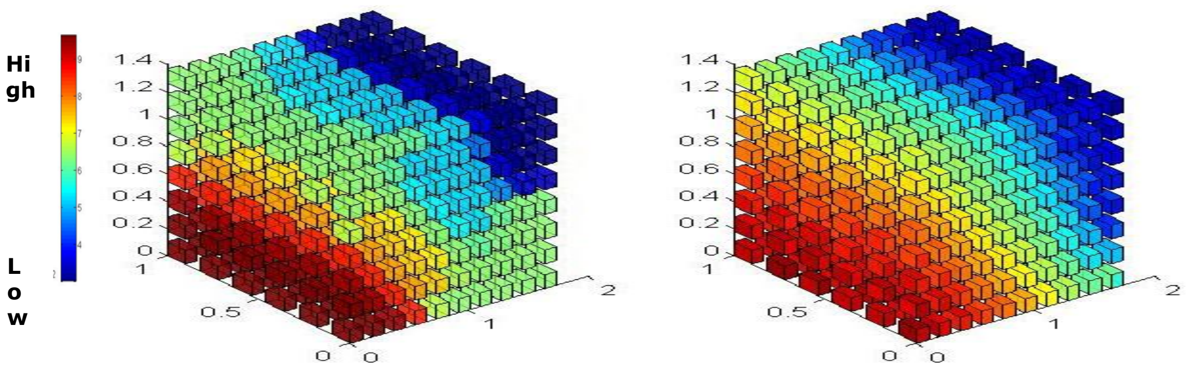


W-noses were deployed in a glass box simulating a 3D ambient. A VOC mixture is let evaporate within the box.



Sensors cross calibrate their Kernel parameters (simulated @ datasink)

3D Reconstruction occurs at Datasink



Istantaneous 3D Ethanol (right) and Acetic Acid (left) concentration images (computed @datasink) using a 4 w-nose deployment in the glass box experimental setup.

CONCLUSIONS

On field WCSN for air quality monitoring: several issue to solve:

Information processing is crucial in many ways

Computational intelligence techniques may help to

- Achieve more precise Multivariate Calibration

- Reduce Drift problems with adaptive strategies

- Extending Module Lifetime (if operating on batteries)

- Reconstruct the pollutant distribution map

THANK YOU FOR YOUR ATTENTION

ACKNOWLEDMENTS:

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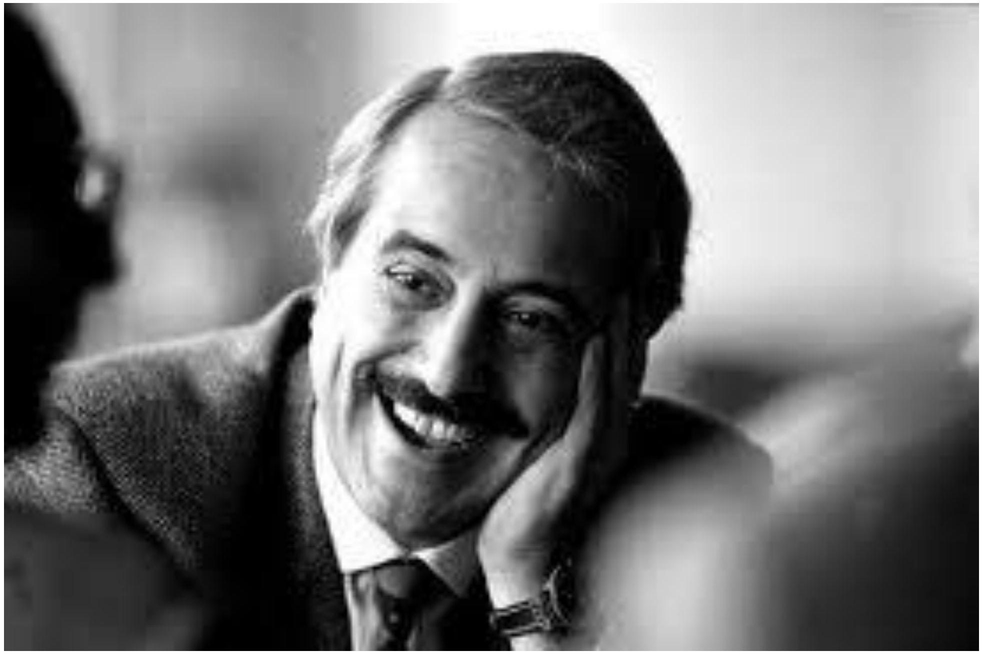

GIOVANNI FALCONE
(AND HIS FELLOWS)
1939-1992

Agenzia nazionale per le nuove tecnologie, l'energia e lo sviluppo economico sostenibile

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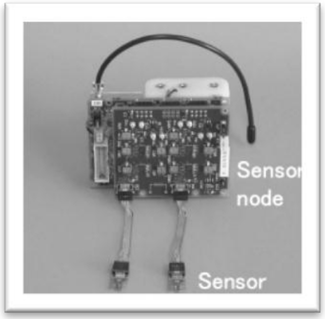
2012

WIRELESS CHEMICAL SENSING MODULES:



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