European Network on New Sensing Technologies for Air Pollution Control and Environmental Sustainability - *EuNetAir*

COST Action TD1105

WGs and MC Meeting at Cambridge, 18-20 December 2013

Action Start date: 01/07/2012 - Action End date: 30/06/2016

Year 2: 1 July 2013 - 30 June 2014 (Ongoing Action)



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Scientific context and objectives in the Action

Computational Intelligence in Modern Air Quality

Research Goal:

- Address Specificity, Stability, Calibration, Energy Management, Deployment Issues with <u>Computational intelligence</u> (Statistical Regression Learning, Evolutionary Computing, Pattern recognition)
- 2. Develop Integrated Sensors/Model as a service architectures capable to cope with mobile distributed social sensing needs (see Poster session)

• Within WG2 and SIG2 objectives:

Develop integrated intelligence for AQC gas sensors and distributed computing



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



A COMMON FRAMEWORK - > COMMON CHALLENGES

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

Actually, We need Low Cost sensors, Low cost platforms to deal with numerosity (stability-sensitivity-specificity trade offs)

- Effective Module Calibration -> (In Lab?, On Field?, Drifts?)
- Calibration Transfer -> (How to deal with sensors diversity, and numerosity)
- Energy Efficiency -> (Operation on Batteries)
- Sensor Fusion & Data Mining -> (How to reach high valued situational awareness)

Our Approach is to explore the possibility of computational intelligence techniques to reduce the impact of these issues.







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 statistica Multivariate calibration (ANN, SVR) of the multisensor system responses.











SINGLE MODULE CALIBRATION:

How to train your platform to operate on Field Building a CI model (ANN) to cope with non-specificity

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!





DRIFT Counteraction (& Training 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 (Co-training) 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.; 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





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



Results:

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



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







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.

Available Facilities

- 3 Climatic Chambers for sensors arrays (2) and sensors nodes (1) characterizations
- Embedded Programming Lab
- Supercomputing (GRID-like) facility
- GIS Models Lab



Suggested R&I Needs for future research

Research directions as R&I NEEDS:

Invest further research energies in:

- Adaptive (cooperative) Drift Counteraction
 - Results are not completely satisfactory (still too much time to ignite)
- Calibration Transfer (Cope with sensor diversity)
 - You cannot repeat the calibration procedure for each node (Costs)

In order to increase reliability of performance estimation and acceptability of the techniques:

MORE MEASUREMENT DATA!!! SHARING DATASETS is a KEY NEED





Thank you for Your kind attention!

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