Low-Cost Sensor Enabled Explosive Detection to Protect High Density Environments

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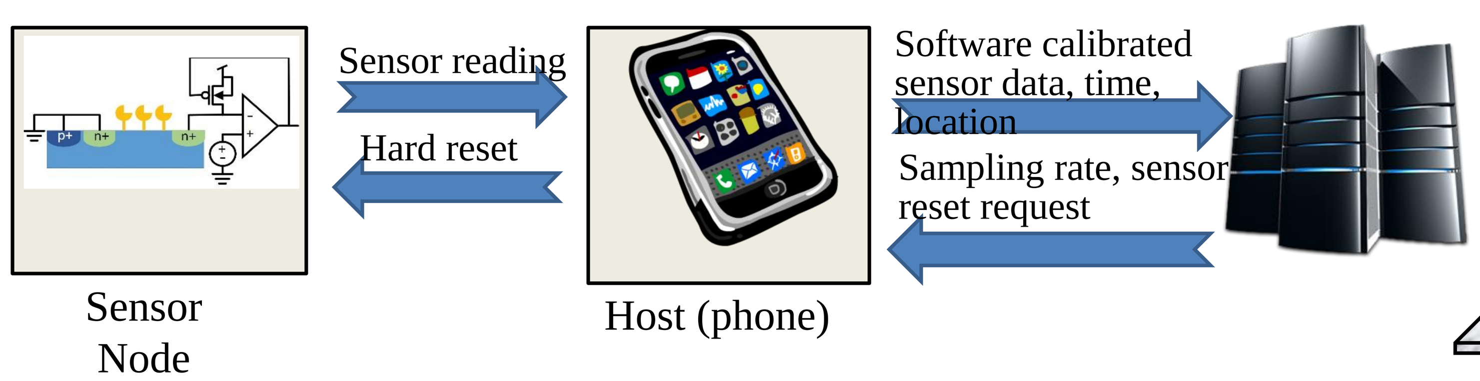
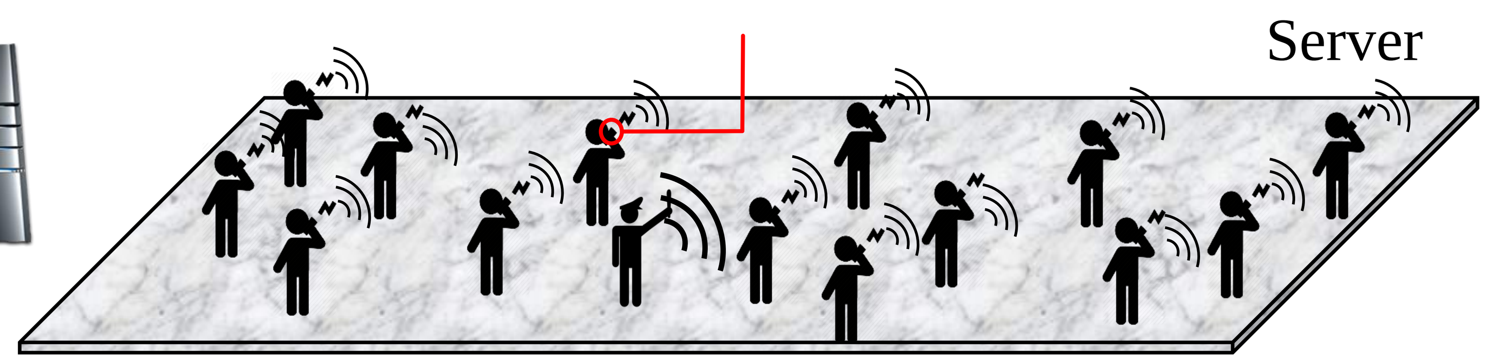
https://sites.google.com/asu.edu/cpsexplosivedetection/





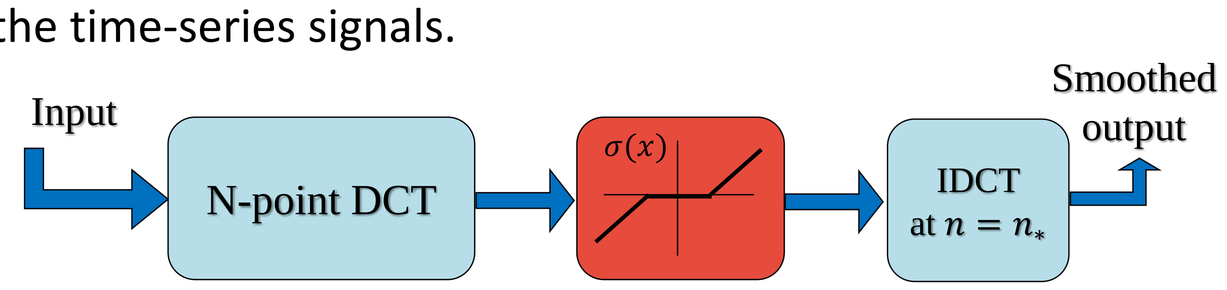
- Protecting large area gatherings from acts of terrorism is challenging due to lack of well controlled access points
- Replaceable sensors that move with the crowd is proposed
- Simple node: sensors paired with cell phones of willing users
- Supernode: officers equipped with higher sensitivity, more reliable devices
- Server: data collection, processing, direction of supernodes, prompt sensor calibration

- Low-cost sensors (ChemFETs) drift and degrade soon after deployment and low accuracy prevents from making decisions based on a single sensor
- Sensors can be calibrated in the field autonomously, but need to know when
- Between calibrations, sensor response needs to be adjusted and decision-making mechanism needs to be robust to prevent false alarms
- Energy consumption should be kept to a minimum
- User experience should not be negatively affected
- No control over movement of nodes and limited number of supernodes that requires minimization of false positives

- This project uses a confluence of emerging technologies to solve problems that previously would require significant resources.
- The project uses low-cost sensors, crowd-sourcing, and data science powered by AI to monitor threats; in this project to focus is explosive threats.
- While the techniques have been developed based on a specific application, the algorithms and methodologies apply to many problems with similar challenges.
- Sensor modeling and calibration methods can be applied to many chemical, mechanical, and even biological sensors.
- Host-level optimization to minimize computation and power overhead apply to problems that require users to donate idle resources
- Privacy and security techniques apply to problems that rely on crowd sourcing without compromising the user's identity.

AI-inspired server-level algorithms to overcome sensor variation and drift

- Servers have more computational power but have to manage many nodes
- We use a novel Discrete Cosine Transform (DCT)-based deep learning network to estimate a baseline level for drifting sensors.
- Temporal Convolutional Neural Network with DCT provides several advantages in terms of no assumptions about the drift characteristics, no assumptions about the sensor response waveform and remove the need to manually extract features from the time-series signals.



- DCT: $F[n_0,k] = \sum_{l=0}^{N-1} f[n_0 - l]\cos\left(\frac{\pi k}{N}\left(N - l + \frac{1}{2}\right)\right), k = 0,1,..,N-1$
- Soft-thresholding $\boldsymbol{\sigma}(\boldsymbol{x}) = \mathbf{sgn}(\boldsymbol{x})\mathbf{Re}\boldsymbol{LU}(|\boldsymbol{x}| - \boldsymbol{b})$, where b is learnable via back-propagation.

- The measured signal is in ***blue***.
- The estimated drift using TCNN-DCT is in ***red***.
- The manually estimated drift is in ***green***.

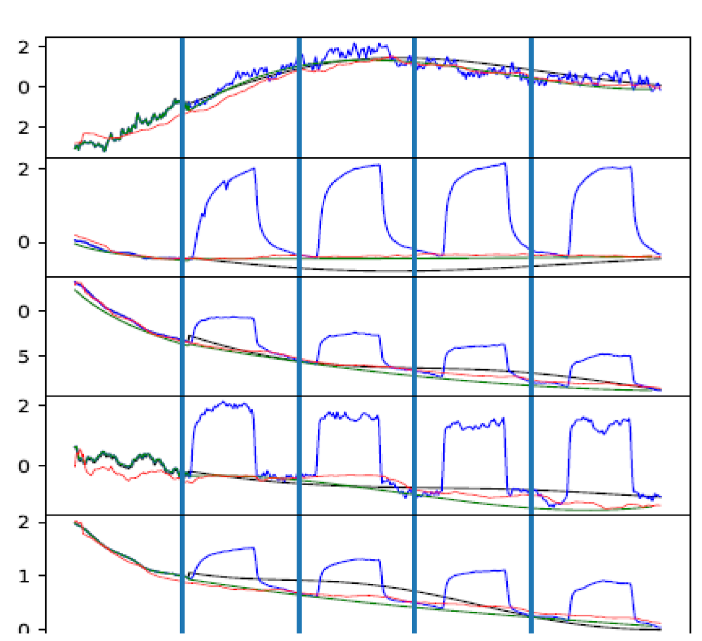


Figure: Drift response learned from one sensor exposed to the target molecule at random intervals

Sensor Design, Evaluation, and Modeling

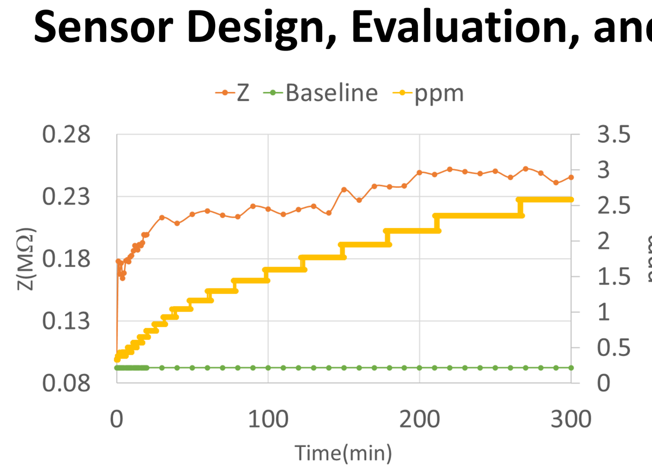


Figure: Sensor response and baseline ppm measured with a commercial sensor

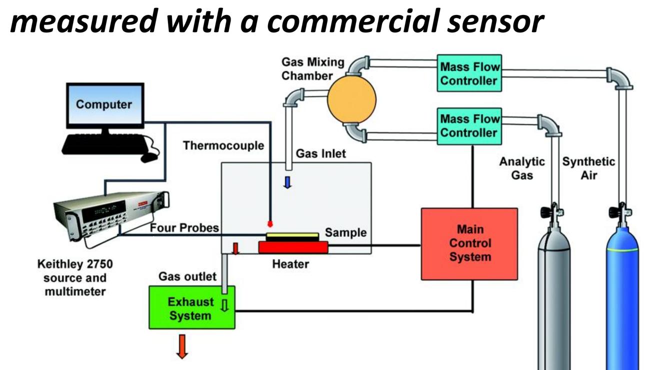


Figure: Experimental set-up designed for sensor characterization

- Low cost sensors suffer from two problems: low sensitivity and drift and lack of reliable operation
- We use a very low-cost process to deposit interdigitated capacitances
- The layers are covered with receptor molecules through a simple soaking process
- Area is kept large (e.g. $10mm^2$) to increase sensitivity
- Host-level algorithms used to calibrate sensor readings based on characterization
- Server-level algorithms used to estimate the sensor response from baseline and differentiate sensor-to-sensor responses using machine learning
- Estimated minimum sensitivity level is 130ppb
- System-level simulations assumed 50ppb: Simulations will now be repeated with this new information

Broader Impacts

- Low-cost semiconductor-based sensors have been deemed as unreliable and not usable beyond lab environment due to drift and process variations
- Developed techniques at the edge and server lever to overcome these problems
  - Modeling of sensor behavior while taking process variations into account
  - Calibration/correction at the sensor edge device (mobile host)
  - Hardware reset and timing of reset based on the functionality of the entire system
  - Server-level outlier detection using AI and feedback to the edge device
- Applicable to many other CPS problems that require collective action
  - Monitoring air pollution or other dangerous emissions
  - Environmental and threat monitoring, such as monitoring for gas leaks, fires, etc.

Broader Impacts on Education

- This project is used to train 10 students at all levels of higher education
  - Undergraduate students via senior design projects to develop the sensor interface software with Arduino module and data collection experiments
  - M.S. students via M.S. theses for sensor modeling
  - Ph.D. students who built the sensors, the experimental set-up, and and collected data with the manufactured sensors
- A new course was developed (UIC) and an existing course was augmented (ASU) with the results of this course.
  - The course "ECE 491 Introduction to Neural Networks" (UIC) uses sensor data collected for this project
  - The course "EEE 528: Sensors, Internet of Things, and Wearable Devices" (ASU) incorporates sensor drift modeling

Broader Impacts on Society

- Protecting the public from threats, intentional or otherwise, is a shared responsibility
- Advances in technology armed ordinary citizens with computation and communication capabilities that are underutilized
- These resources can be retooled transparently to solve threat detection problems

	Stationary	Crowd-sourced
Cost per sensor	\$10,000	\$5
Detection range	20m	1m
Protect K-12 school	\$1M	\$5K
Protect marathon	\$1B	\$100K

This can be achieved at low cost by using mobility of nodes (users with host devices) to cover a much wider range than the sensors can.

Examples beyond the primary application domain: Detecting air pollution, gas leaks