

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

UC San Diego

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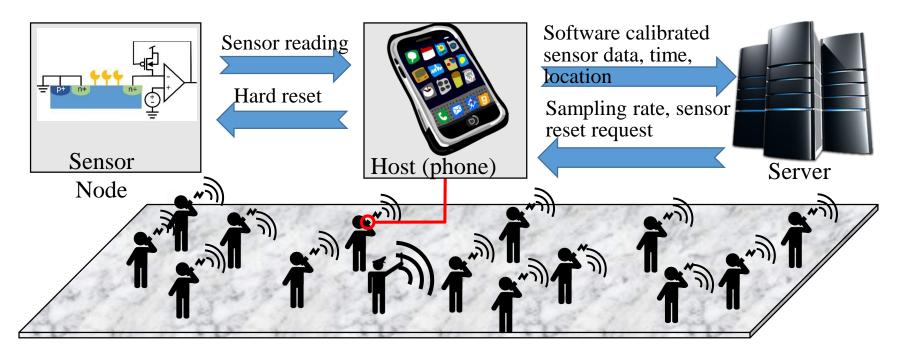


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Introduction

- 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, calibration prompt of sensors



- Challenges
- Low-cost sensors (ChemFETs) drift and degrade soon after deployment
- Low accuracy prevents from making decisions based on a single sensor
- Sensors can be calibrated in the field autonomously, but need to know when
- Energy consumption should be kept to a minimum
- User experience should not be negatively affected
- No control over movement of nodes
- Limited number of supernodes

Detection Algorithm

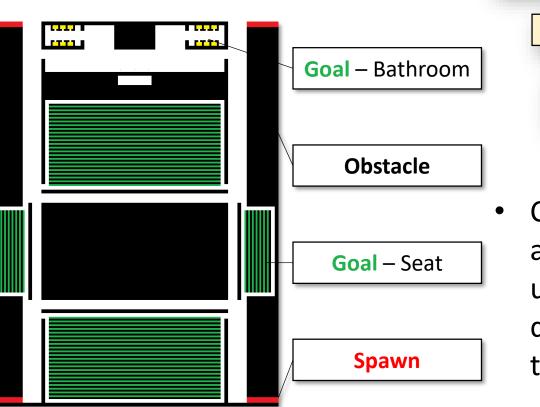
- Use spatial and temporal locality (data time and location stamped)
- Use multitude of sensors to check one another and lower detection distances
- Validator Based Detection
 - Once positive result is observed, it is corroborated with other sensors in the vicinity (spatially and temporally)
- The number of required validators adjusted wrt density
- Validation only by unique nodes
- Grid Average Based Detection
- Use maximum detection distance to divide coverage area into grids
- Moving average reading compared to threshold
- Time duration of moving average adjusted wrt density

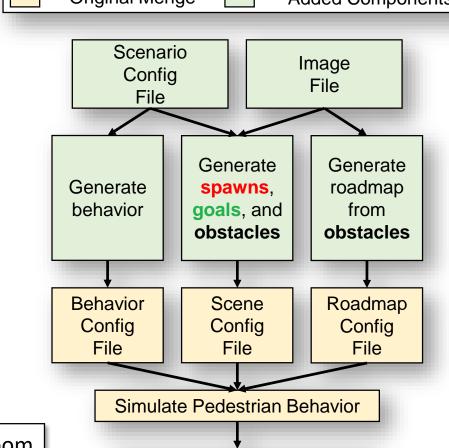
Sensor Hard Reset

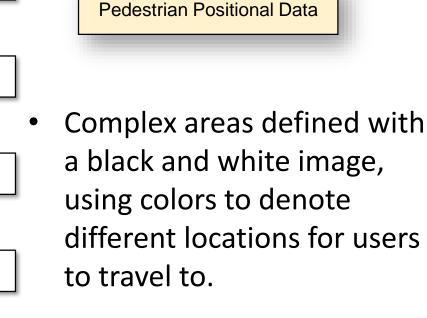
- Sensor hard reset
 - Due to accumulation mechanisms, sensor sensitivity continuously drifts and del
- Hard reset reverses accumulation, brings the sensor back to fresh status
- Hard reset takes sensor off-line for several seconds
- Hard reset has an energy cost that is roughly equal to 2x conversion energy
- Two mechanisms to initiate sensor hard reset
 - Host initiated reset
 - Host maintains internal parameters
 - Host initiates sensor hard reset if the sensitivity degrades below 50% of its original value
 - Host initiates sensor hard reset if the maximum error term exceeds detection threshold
 - Server initiated reset
 - Server maintains moving grid averages of coverage area
 - If a node deviates more than 6σ of the grid readings, the node is deemed to be an outlier
 - Server sends a request to the host to initiate hard reset

Crowd Movement Simulator

- Create scenario generator for **MENGE Crowd Simulator to** automate the generation of complex crowd movements to enable realistic simulation of large populations.
- Moving pedestrians follow probabilistically defined state machine and automatically route to destinations.







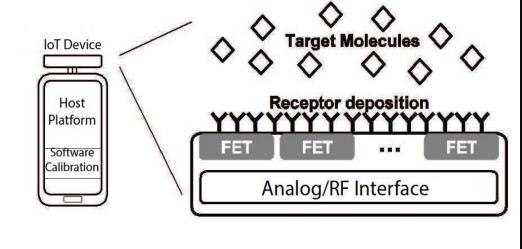
Sensor Design and Host Calibration

- ChemFETs are chosen due to
- Very low cost manufacturing (<10c per sensor)
- Reasonable sensitivity (10ppb range)
- CMOS compatible (sensor and basic AFE can be integrated)
- · Threshold voltage changes via fast, slow, and long-term response drift

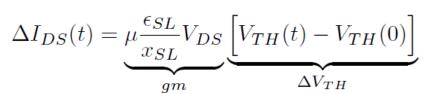
$$\Delta V_{TH}(t) = \Delta V_{TH_{(F,S)}}(t) + \Delta V_{TH_{(D)}}(t)$$

$$\Delta V_{TH_{(F,S)}} \rightarrow fast, slow \ response \ drift$$

$$\Delta V_{TH_{(D)}} \rightarrow long - term \ response \ drift$$



• I_{DS} is related to shift in V_{TH} under constant V_{GS}



 $\epsilon_{SL} \rightarrow dielectric constant$

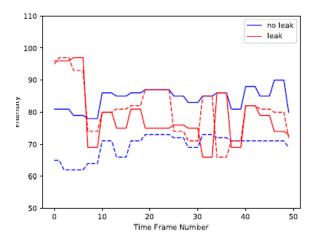
 $x_{SL} \rightarrow thickness \ of \ surface \ insulator$ $V_{DS} \rightarrow drain - source\ voltage$

- Deviation in drain current (ΔI_{DS}) as a function of
 - Concentration of the target molecule
 - Temperature
 - Time

- $V_{TH} \rightarrow threshold\ voltage$
- $R_T = c_1 \cdot e^{-\frac{c_2}{T}}$ $R_{pH} = c_3 \cdot pH$
 - R_T and R_{nH} are the drift rates c_1 , c_2 , and c_3 are drift rate coefficients
 - f_r , s_r , and d_r are the drift coefficients τ_f , τ_s , and τ_d are the time constants

Gas Leak Detection Using Uncalibrated Sensors

- Both chemical and infra-red (IR) sensors generate distinct responses under similar conditions because of sensor drift and/or noise.
- We process time-series sensor signals using deep neural networks (DNN).
- Two novel neural networks (NN) are developed.
- We consider the task of Gas leak detection using infrared-VOC data.



0	10	20	30	40	50	AddNet
	NO CONTRACTOR	Time Frame	e Number			DiscGAN
] —					

Recognition Results for Gas Leak Detection							
Model	No-Gas Accuracy	Gas-Leak Accuracy	Total Accuracy				
Ordinary CNN	98.0%	94.2%	96.1%				
AddNet	99.1%	97.3%	97.1%				
DiscGAN	99.0%	97.1%	98.1%				

Robust DiscGan NN Advantageous in the case of unbalanced dataset Phase 1: Unsupervised adversarial training as

in generative adversarial NNs (GANs) only uses the underbalanced class data as

real data Generator tries to fool the discriminator by creating synthetic data resembling the real data

Phase 2: Supervised training of the discriminator as a classifier Uses data from both classes.

Energy-Efficient Additive NN

Replace dot-product with vector addition with sign compensation $w \oplus x = \sum \operatorname{sgn}(w_i x_i)(|x_i| + |w_i|)$

Event Based Detection Scenarios

- Design and implement event-based CPS simulator to accurately and efficiently simulate new detection algorithms, communication requirements, and sensor drift models.
- Utilize movement and chemical concentration simulations as inputs to improve real world correlations. Statistics processing allows for design space exploration and validation.

