

DETECTING GAS VAPOR LEAKS THROUGH UNCALIBRATED SENSOR BASED CPS

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Abstract

- CPS comprised of ordinary people or first responders is proposed to detect gas vapor in open air.
- This CPS will use low-cost sensors coupled to smart phones or mobile devices.
- The efficacy of CPS hinges on its ability to address technical challenges stemming from the fact that sensors may produce different results under the same conditions due to sensor drift, noise, and/or resolution errors.
- The proposed system makes use of time-varying signals produced by sensors to detect gas leaks. Sensors sample the gas vapor level in a continuous manner
- Time-varying sensor data is processed using deep neural networks to detect gas vapor leaks.

Sensors

- Chemically-sensitive Field Effect Transistors (ChemFETs)
- Electrochemical Impedance Spectroscopy (EIS) based sensors
- Chemical sensors suffer from sensor drift: sensor signal decay over time in an unpredictable manner.
- Infrared Sensors (some VOC compounds and ammonia absorb infrared light at Medium Wave InfraRed (MWIR) and Long Wave InfraRed (LWIR) bands).
- It is not possible to fix a threshold to detect gas vapor because of sensor drift and IR light reflections
- All of the above sensors produce time-varying signals

Challenges

Gas vapor detection algorithm should be

- Energy-efficient
- High accuracy

Proposed Methods:

- Multiplication-free Convolutional Neural Network: AddNet
- Discriminator of Generative Adversarial Neural Network.

AddNet: Multiplication-free Vector Product Based Neural Network

- Convolutional Networks (ConvNet) have high generalization capabilities in classification tasks involving time-series data.
- Nevertheless, ConvNets are computationally expensive
 - Millions of add-multiply operations needed during inference
- We replace vector multiplication in artificial neural network by a special operation

Let a and b be two real numbers. We define the multiplication-free operator as follows:

$$a \oplus b = \text{sgn}(a)\text{sign}(b)(|a| + |b|)$$

Let x and y be two vectors :

$$x \oplus y = \sum_i \text{sgn}(x_i)\text{sign}(y_i)(|x_i| + |y_i|)$$

No multiplication is performed. Instead, regular addition and sign operations are performed.

In AddNet, feedforwarding pass equation become

$$f(w^T x + b) \rightarrow f(\alpha(w \oplus x + b))$$

x is output previous layer, f is non-linear activation, b is bias and w is the weight vector, α is a real-valued scalar. The nonlinear activation function f is RELU so α is the slope of RELU.

Discriminator of Generative Adversarial Network (GAN) as Classifier

- GANs has become the benchmark in image synthesis. Typical GAN consists of two networks: generator and discriminator.
 - Generator tries to generate data that mimics the real data, whereas the discriminator tries to tell whether its input data are real or fake.
- Both networks are trained jointly so as to optimize the following objective function:

$$\max_{\theta_D} \min_{\theta_G} \sum_i \log(D(x^i)) + \sum_i \log(1 - D(G(z^i)))$$

x^i is a real data point, $G(z^i)$ is a fake generated sample, $D(\cdot)$ is the discriminator prediction whether the corresponding input is real or fake, θ_G is the generator parameters, and θ_D is the discriminator parameters

- In our approach, we carry out two-phase training as follows:
 - Phase 1 (Unsupervised): Train both generator and discriminator with data corresponding to a specific class. Optimize the typical GAN objective function.
 - Phase 2 (Supervised): train only the discriminator with data from both classes as a classifier. The objective is to minimize binary cross-entropy:

$$CE := -\frac{1}{N} \sum_i (1 - t^i) \log(1 - D(x^i)) + t^i \log(D(x^i))$$

t^i (=0 or 1) is the true label of the data point x^i and $D(\cdot)$ is the prediction of the now-classifier D

- We also developed a GANwith AddNet discriminator

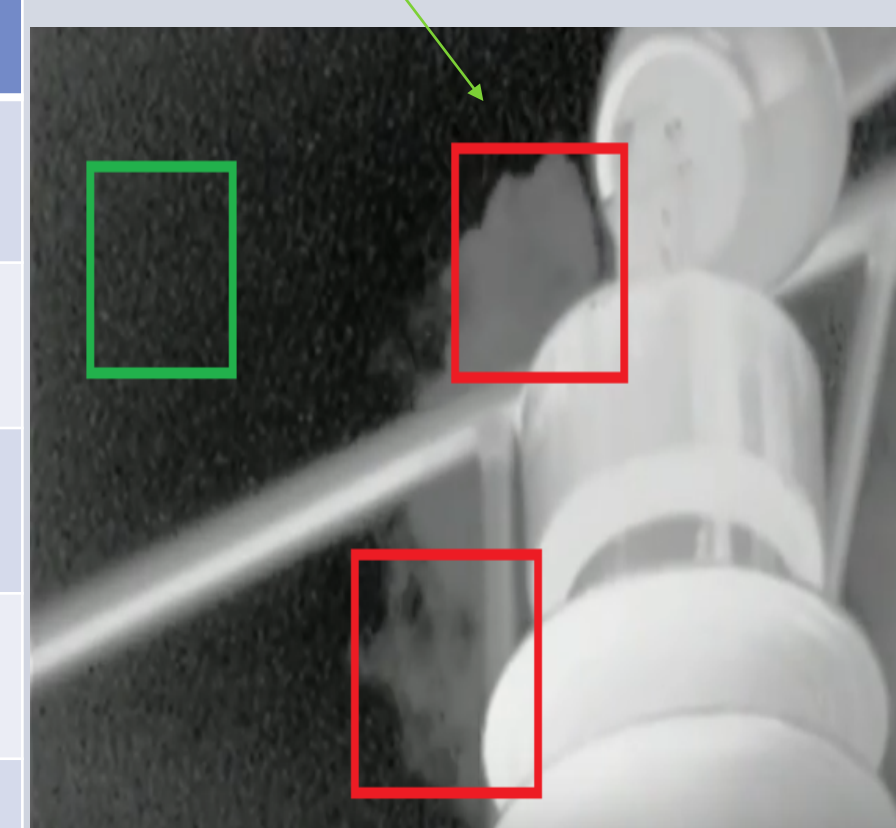
Dataset and Experimental Results

Experiment 1

- Data set consists of infrared sensing signals of VOC gas leaks in open air and clean air recordings (two classes).
- We trained our model with a greatly imbalanced dataset (8000 clean-air vs. only 50 gas-leak training samples).
- Recognition rates

Model	No-gas Accuracy	Gas-leak Accuracy	Total Accuracy
ConvNet (dropout 50%)	98.3%	95.8%	97.1%
ConvNet (no dropout)	98.0%	94.2%	96.1%
AddNet (dropout 50%)	98.2%	96.0%	97.1%
AddNet (no dropout)	99.1%	97.3%	98.2%
Discriminator of GAN	99.0%	97.1%	98.1%
AddNet discriminator	99.6%	98.4%	99.0%

VOC gas leak in an IR image



Experiment 2

- Publicly available sensor drift dataset collected at UCSD, which is obtained by exposing an array of 16 different chemical sensors to 6 different types of gas mixtures (ammonia, acetone, ethylene, ethanol, toluene and acetaldehyde)
- 8 features are extracted for each sensor, thus 128 features constitute each data point. Features are : maxima and minima of exponentially moving average (6), (un)normalized maximum resistance change (2).
- dataset recorded by conducting experiments over 3 years.
- Sensors suffer second-order drift over time. Therefore, distinguishing different gas mixtures become very challenging.

Batch ID	SVM Classifier Ensemble	Multi-Layer Perceptron (MLP)	AddNet-MLP	Discriminator of GAN	AddNet Discriminator
Batch 3	87.8	98.6	98.6	98.3	97.8
Batch 4	90.6	83.8	75.1	71.4	69.6
Batch 5	72.1	99.5	99.4	98.4	98.9
Batch 6	44.5	74.9	75.9	72.3	73.9
Batch 7	42.5	59.8	57.4	61.5	66.3
Batch 8	29.9	34.0	34.0	62.3	58.8
Batch 9	59.8	31.6	38.9	63.2	63.8
Batch 10	39.7	47.3	54.3	43.8	44.5

Conclusions

- We analyze the time-varying signal waveforms that sensors generate using neural networks to address the problem of gas sensor drift.
- We use the AddNet and the discriminator of a GAN as a classifier.
- AddNet produces comparable results to a regular deep neural network without the need to perform vector multiplication operations, which require energy consuming GPU processing.
- The weights of AddNet are highly compressible, with no resultant degradation in performance.

Model Accuracy	Weight Compression (smallest K%)					
	0 (no compression)	16.1	19.7	67.4	76.8	86.6
AddNet	98.9	97.2	97.9	98.0	97.1	61.3
ConvNet	99.8	67.4	-	-	-	-

- AddNet can be used in mobile devices forming such CPS systems so as to deliver accuracy and frugality at the same time.

Future Work

- We will collect our own chemical sensor data
- We will implement AddNet on low-cost microprocessors
- We will investigate domain adaptation techniques by utilizing new sensor readings in sensor drift problem.

References

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