Wireless Sensor Networks for Detection of IED Emplacement

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A very hard problem

- Improvised explosive devices (IEDs) are a serious problem in Iraq and Afghanistan.
- We need many methods to address them, including surveillance.
- Automated visual surveillance suffers from cost, occlusion problems, lesser effectiveness at night, and difficult challenges in image processing.
- Non-imaging sensor networks could supplement visual surveillance with magnetic, infrared, acoustic, and seismic data.
- Non-imaging sensors could alert us when behavior is sufficiently suspicious to turn on cameras or when to search an area.

Path suspiciousness clues

In work with surveillance video, we tested seven clues to suspicious behavior:

- infrequency of visit to a location
- atypicality of speed
- atypicality of the velocity vector
- nonzero norm of the acceleration vector on any of several time scales. We used:

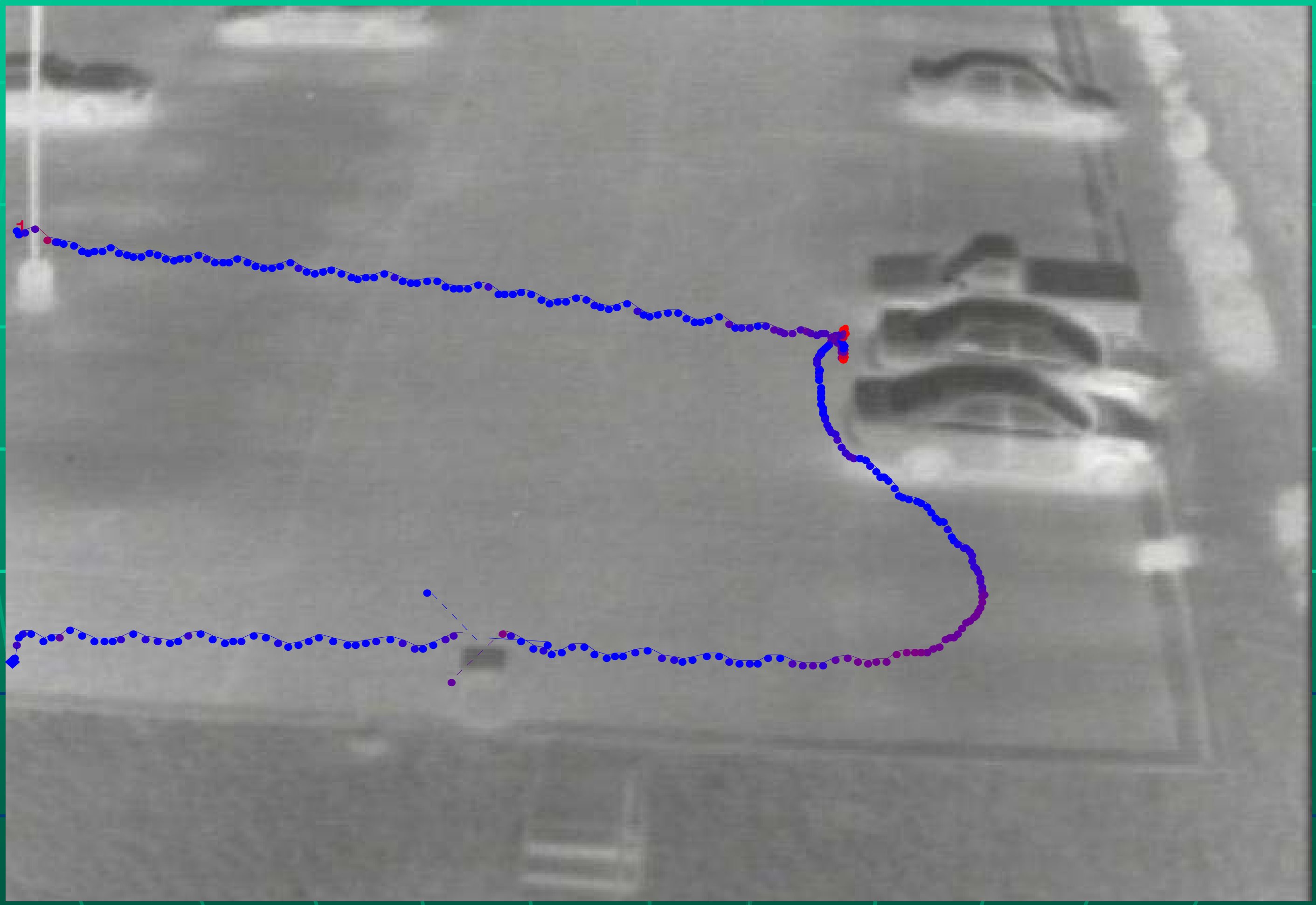
$$a(d) = (1/d(N-2d)) \sum_{i=d+1}^{N-d} \left\| -x(i-d) + 2x(i) - x(i+d) \right\|$$

- fraction of apparent concealment
- shortness of the path
- "contagion" by other nearby suspicious paths

The acceleration norm was by far the best in tests of surveillance of a parking lot (ARL data).

Computed acceleration norm (redness) on a path

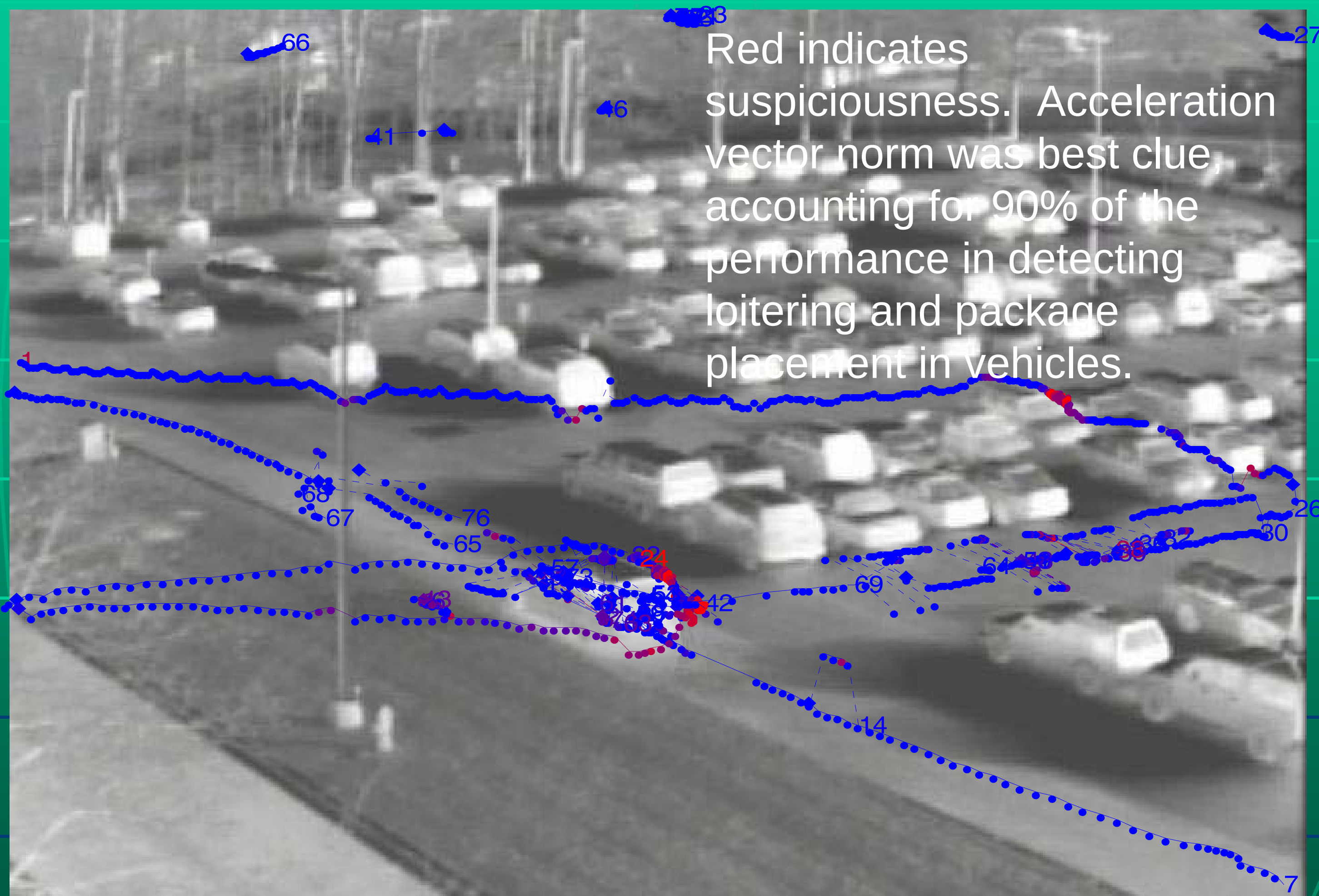
Suspicious movements for rf20050110_1 72844fi (Flag: 0)(Scale: 1)(pictures 13 through 336)



initial location: pathID(pic#)(ave of max and ave suspicion)
suspicion(low...high): blue...red

A more complicated video sequence

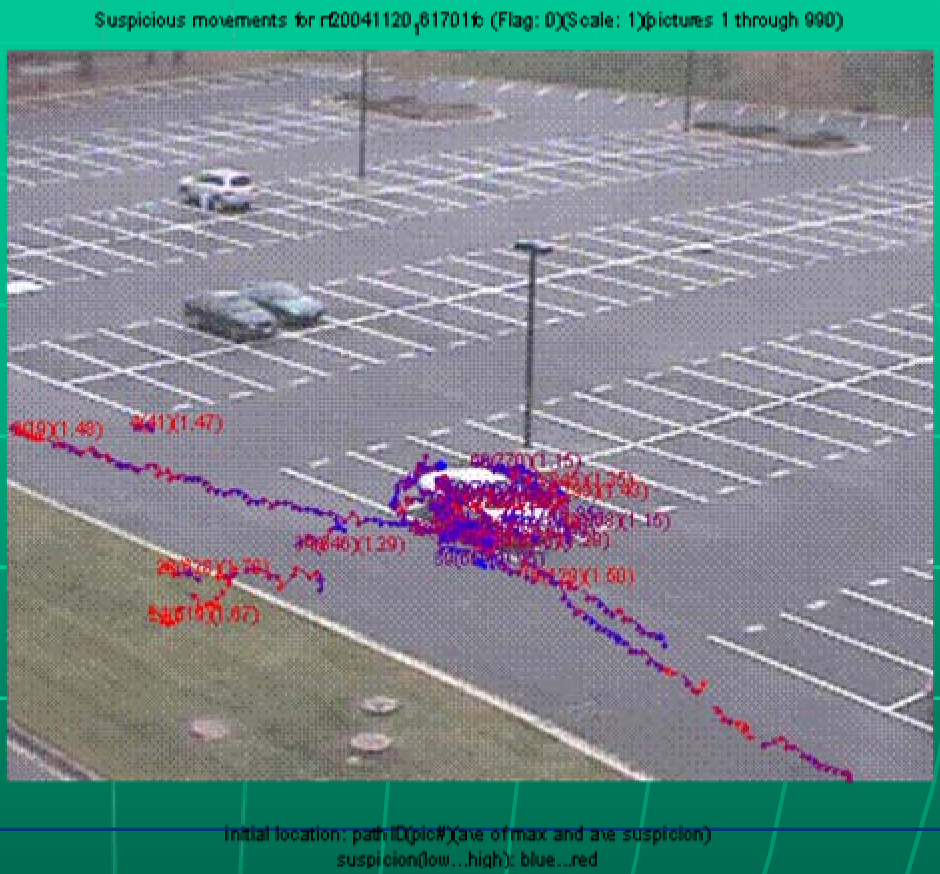
Suspicious movements for rf20041216$_1$50734fi (Flag: 0)(Scale: 1)(pictures 1 through 440)



initial location: pathID(pic#)(ave of max and ave suspicion)
suspicion(low...high): blue...red

Suspiciousness clue of contagion

- Suspicious people and objects make more suspicious the other objects with which they associate.
- E.g.: a box left on ground makes suspicious the people leaving it.



The acceleration norm provided 90% of the performance

		Color Sequences			Infrared Sequences		
		Precision	Recall	F-score	Precision	Recall	F-score
All factors	Suspicious objects (11)	.45	.70	.55	.71	.80	.75
	Loitering (16)	.69	.74	.71	.89	.79	.84
	Other behaviors (26)	.61	.67	.64	.68	.63	.63
	Total	.60	.69	.64	.61	.72	.66
Accel. factor	Suspicious objects (11)	.52	.83	.64	.47	.87	.61
	Loitering (16)	.67	.57	.62	.61	.62	.62
	Other behaviors (26)	.53	.50	.51	.67	.46	.55
	Total	.57	.61	.59	.59	.62	.60

Localization from signal strengths alone

- Many signals follow an inverse square law with distance.
- Given observed signal strengths at different sensors at the same time, their ratios indicate the ratio of squares of distances.
- For two sensors, the locus of source locations is a circle defined by:

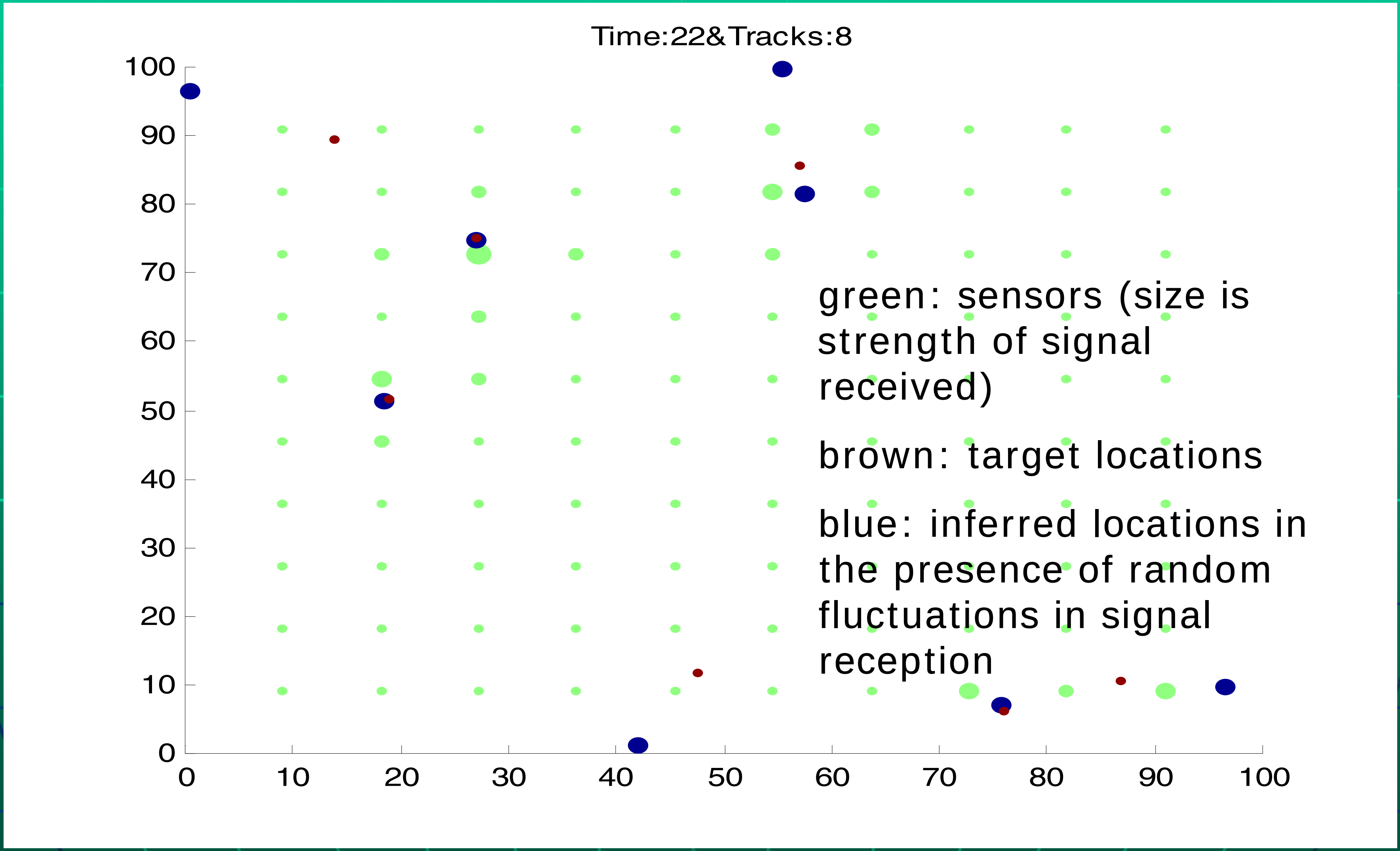
$$x_c = (s_1 x_1 - s_2 x_2)/(s_1 - s_2), y_c = (s_1 y_1 - s_2 y_2)/(s_1 - s_2),$$

$$r = \sqrt{[s_1 s_2((x_{s1} - x_{s2})^2 + (y_{s1} - y_{s2})^2)/(s_1 - s_2)^2] - h^2}$$

A sensor-network simulator

- Real sensor networks have varying performance based on environmental conditions and phenomena being sensed.
- A simulation allows us to isolate inherent problems of the network design and its algorithms.
- Our simulation has demonstrated the ill-conditioned nature of localization in an inverse-square-law sensor grid – a weakness of GPS.
- Our simulation results also provide upper bounds on performance of real networks.

Display of our sensor-network simulator



Simulation results (dist. & strength errors)

	grid	v sd	s sd	si sd	h dev	1 track	2 tracks	4 tracks	8 tracks
Track locations are signal peaks	10x10	0	0	0	0	1.826, 0.324	3.189, 0.541	5.738, 0.955	10.935, 1.544
Track locations from circle est.	10x10	0	0	0	0	0.000, 0.000	0.369, 0.026	1.378, 0.108	6.042, 0.447
Same	10x10	5	2.5	0	0.3	0.000, 0.000	0.278, 0.021	1.217, 0.102	5.186, 0.437
Same, estimation done twice	10x10	5	2.5	0	0.3	0.000, 0.000	0.278, 0.024	1.217, 0.114	5.186, 0.459
Same, est. then traditional optimization	10x10	5	2.5	0	0.3	0.000, 0.000	1.926, 0.020	9.093, 0.189	24.698, 0.959
Same, circle estimation	4x4	5	2.5	0	0.3	0.000, 0.000	1.841, 0.063	9.275, 0.309	28.292, 1.094
Track locations are signal peaks	10x10	5	2.5	2	0.3	1.851, 0.324	3.042, 0.521	5.411, 0.869	10.551, 1.472
Same, circle estimation	10x10	5	2.5	2	0.3	0.805, 0.059	1.563, 0.108	3.109, 0.216	7.405, 0.538

Localization from time of arrival

- GPS uses this – but algorithms need to be different for sensors since time accuracy is less.
- We use gradient descent with:

$$\partial G_D / \partial x = \sum_{i=1}^{N} \sum_{j=i+1}^{N} 2 * \operatorname{sgn}(E_D) *$$

$$[((x - x_i) / \sqrt{(x - x_i)^2 + (y - y_i)^2} - ((x - x_j) / \sqrt{(x - x_j)^2 + (y - y_j)^2})]$$

$$\partial G_D / \partial y = \sum_{i=1}^{N} \sum_{j=i+1}^{N} 2 * \operatorname{sgn}(E_D) *$$

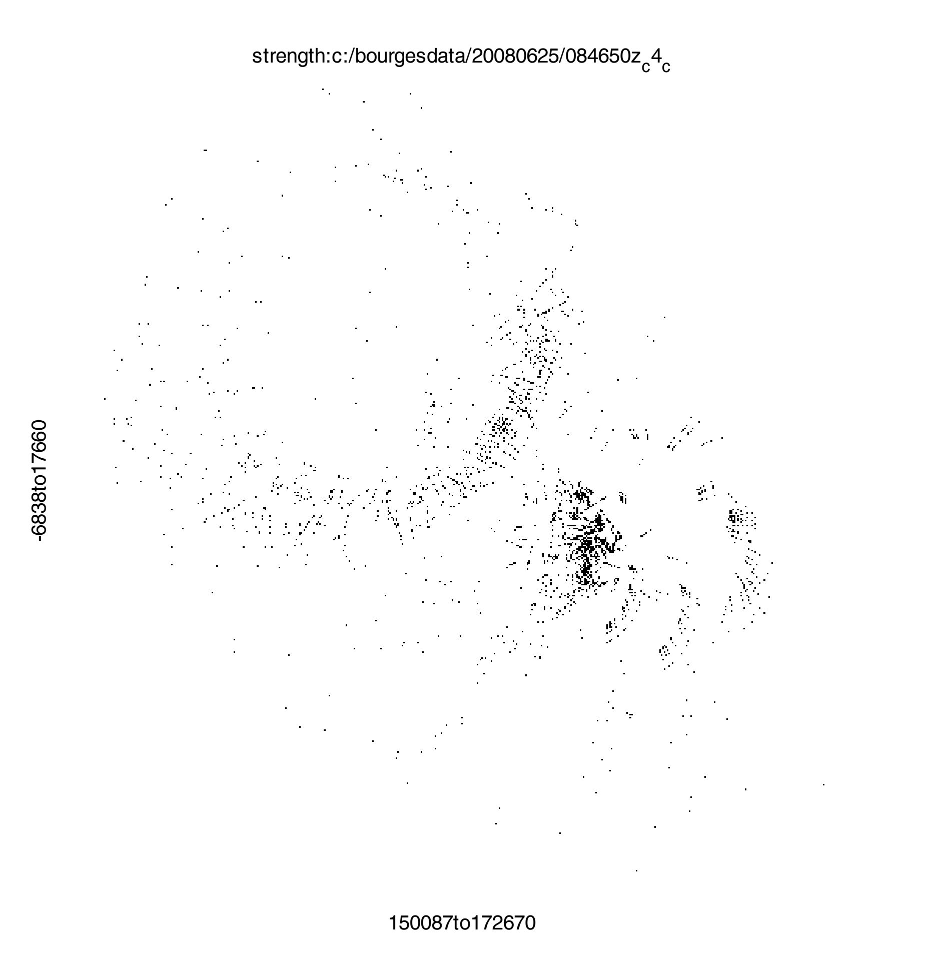
$$[((y - y_i) / \sqrt{(x - x_i)^2 + (y - y_i)^2} - ((y - y_j) / \sqrt{(x - x_j)^2 + (y - y_j)^2})]$$

Experiments with ARL acoustic data

- We obtained audio of explosions recorded by ARL from a number of microphones simultaneously at different distances, at 40,000 hertz.
- We calculated average deviation of signal from its mean in each 0.1-second interval.
- All intervals whose energy exceeded the mean were identified as peaks except where preceded by another.
- For each peak we computed:
  - Height
  - Largest frequency of the Fourier spectrum 0.5-50 hertz
  - Log of the Fourier magnitude at that peak
  - Mean log of the Fourier magnitude over its spectrum
- If we obtained more than five peaks from a sensor-event pair, we used only the five largest.
- These features have been shown helpful in characterizing low-frequency events like explosions.
- We also extracted wavelet parameters but these did not prove helpful.

Time-of-arrival localization errors

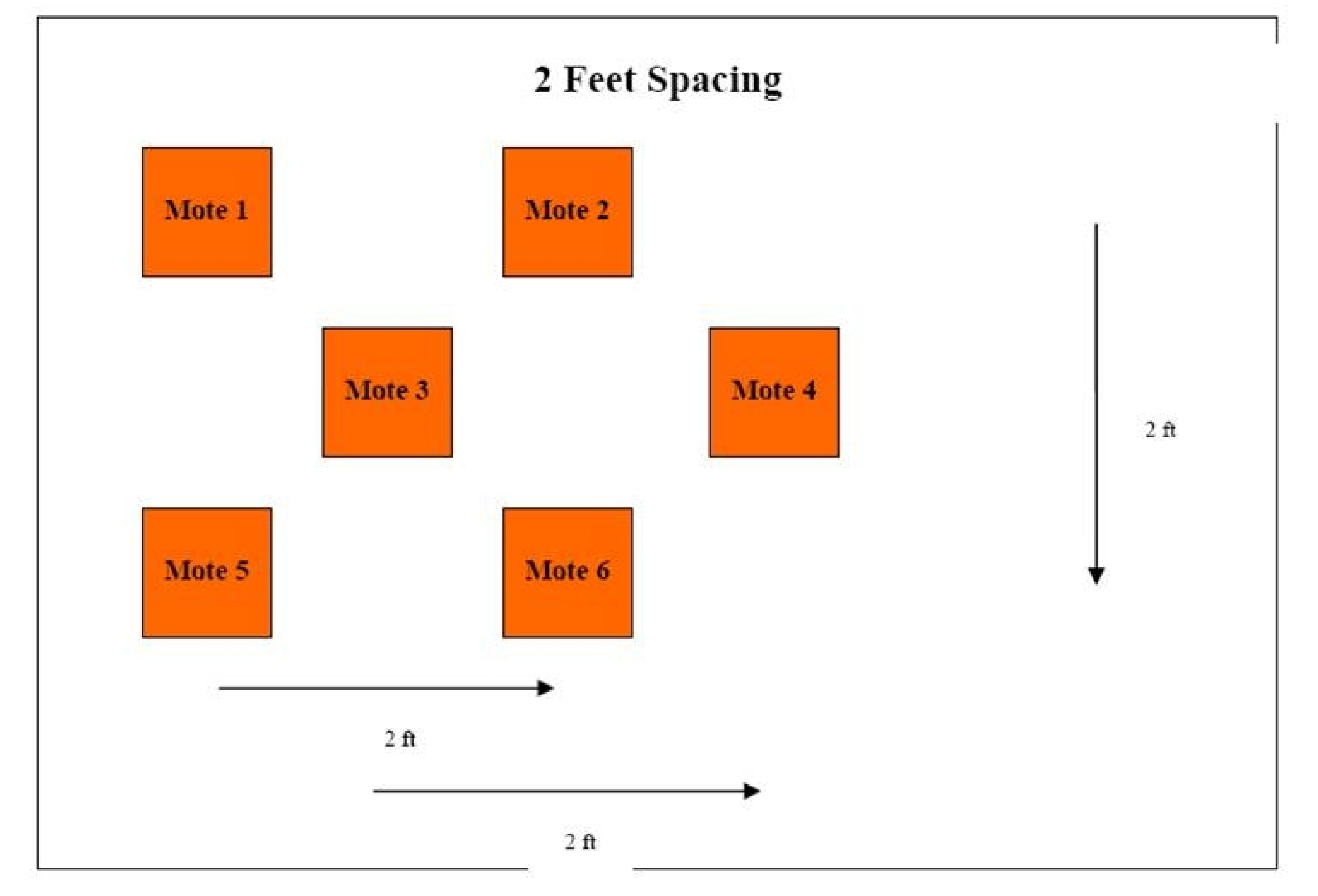
- Image shows localization of a source from signal strength of inferred peak matches.
- Low accuracy of peak matching hurt localization.
- Problems were caused by echoes and shock waves.
- Performance was worse for time-of-arrival position estimation.
- Footsteps should have less such problems.



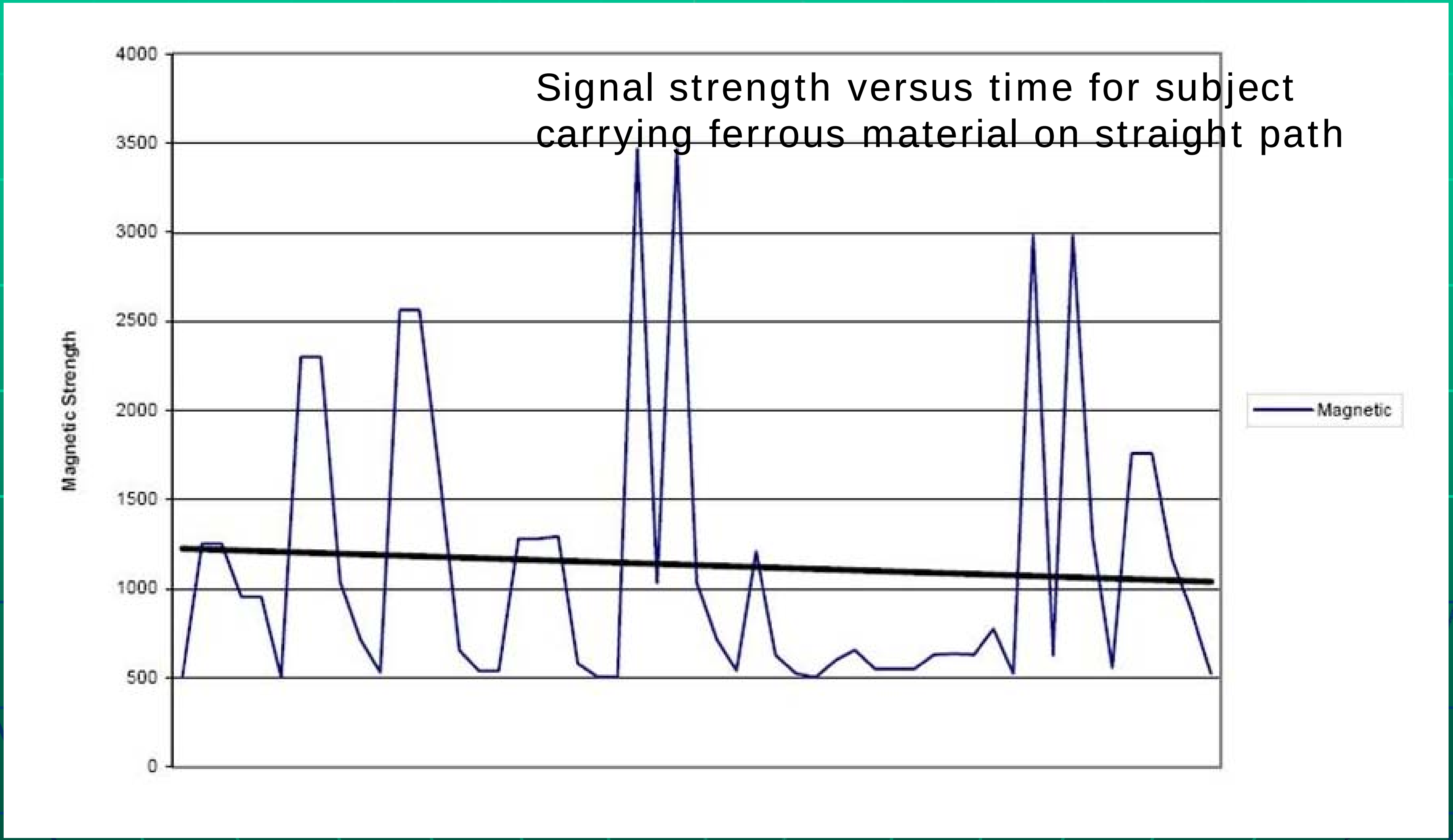
Sensor-network configuration experiments

- We also did experiments with Crossbow sensors to determine relationships between distance of source and accuracy.
- We set up different configurations and measured ability to detect ferromagnetic materials using the magnetic sensors.
- This allows us to make specific recommendations for sensor network design.

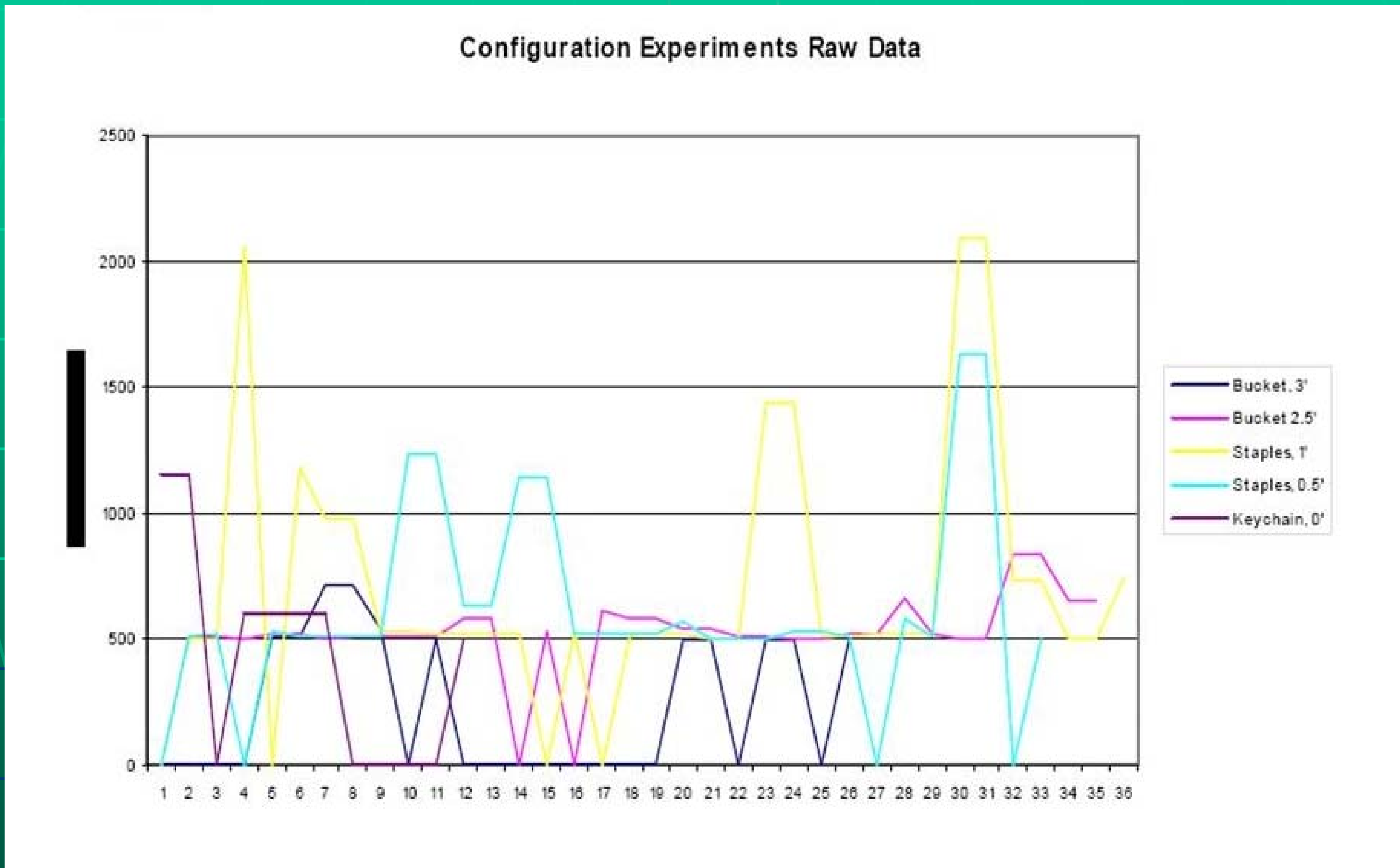
Example configuration tested



The magnetic sensors are definitely nonlinear



Nonlinearity in quantity of ferrous material



Conclusions about the real-sensor experiments

- These magnetic sensors are too nonlinear to be useful for localization by signal strength or time of arrival.
- But in sufficient quantity, they could indicate a probability distribution of location.
- Combined with infrared data, area could be reduced.
- Combined with acoustic or seismic data, we could use our optimization methods to significantly improve localization accuracy.

Ongoing work

- We are focusing on acoustic and infrared detection as the most useful for finding IED-related behavior.
- We will fit formulae for the simulation from experiments, then run simulation to fit performance to parameters.
- Tracking one person is not hard – how well we can detect suspicious behavior in crowds?
- Acceleration vectors are harder to measure in a crowd, but anomalous values can still be detected.
- Similarly, other suspicion factors are averaged but not concealed in crowds.