Flexible Human-Machine Information Fusion and Perception in Contested Environments

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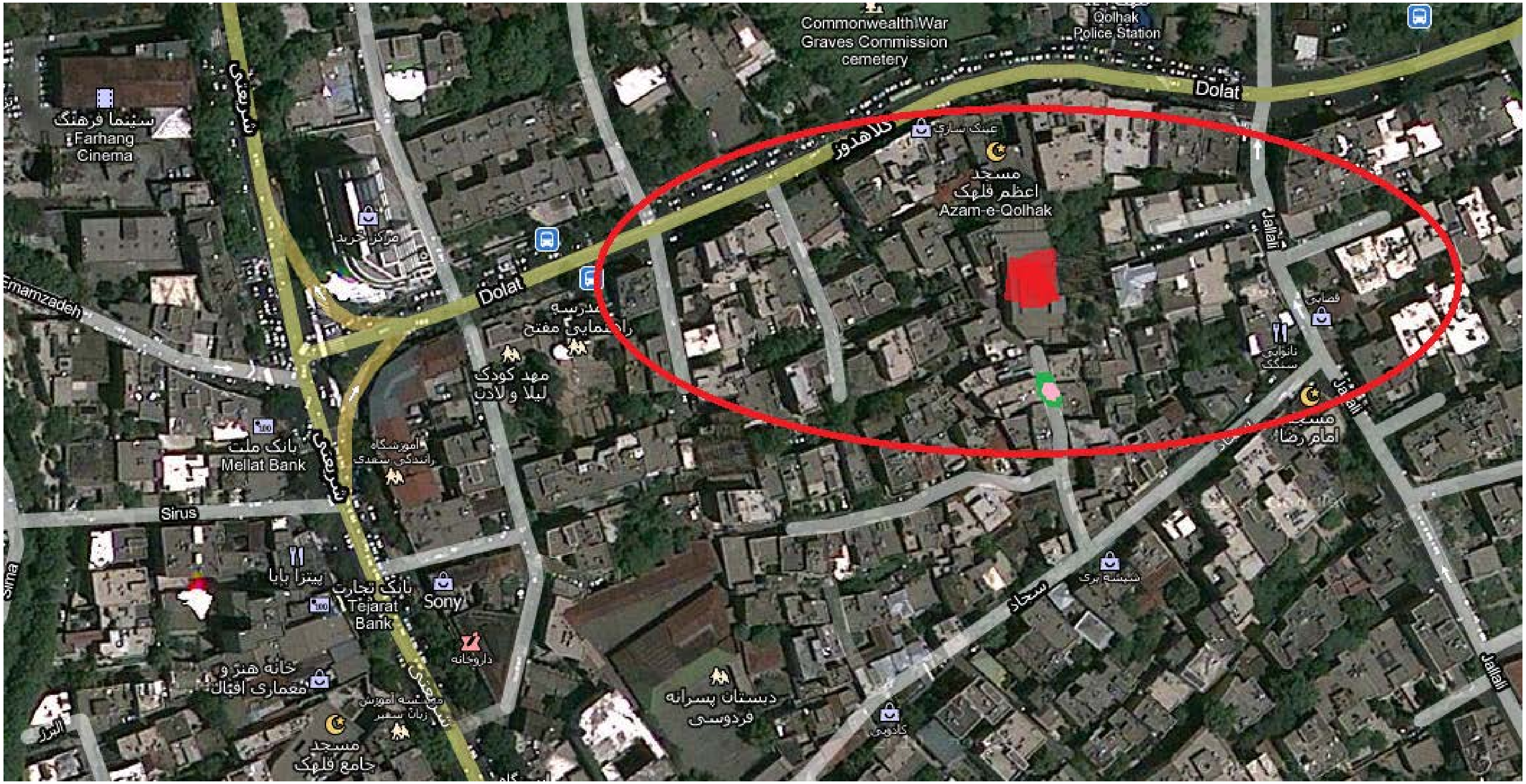
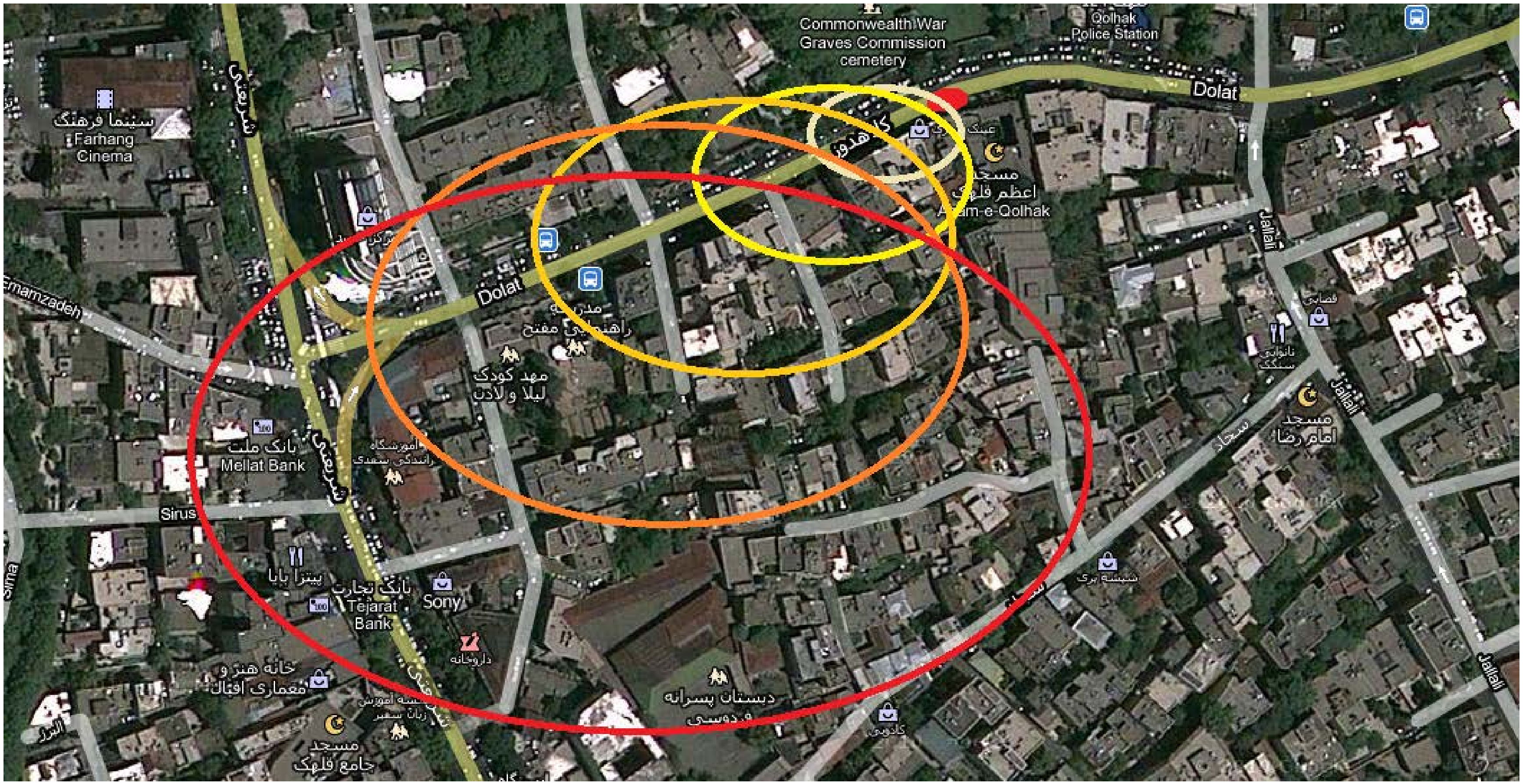
Urban Target Tracking



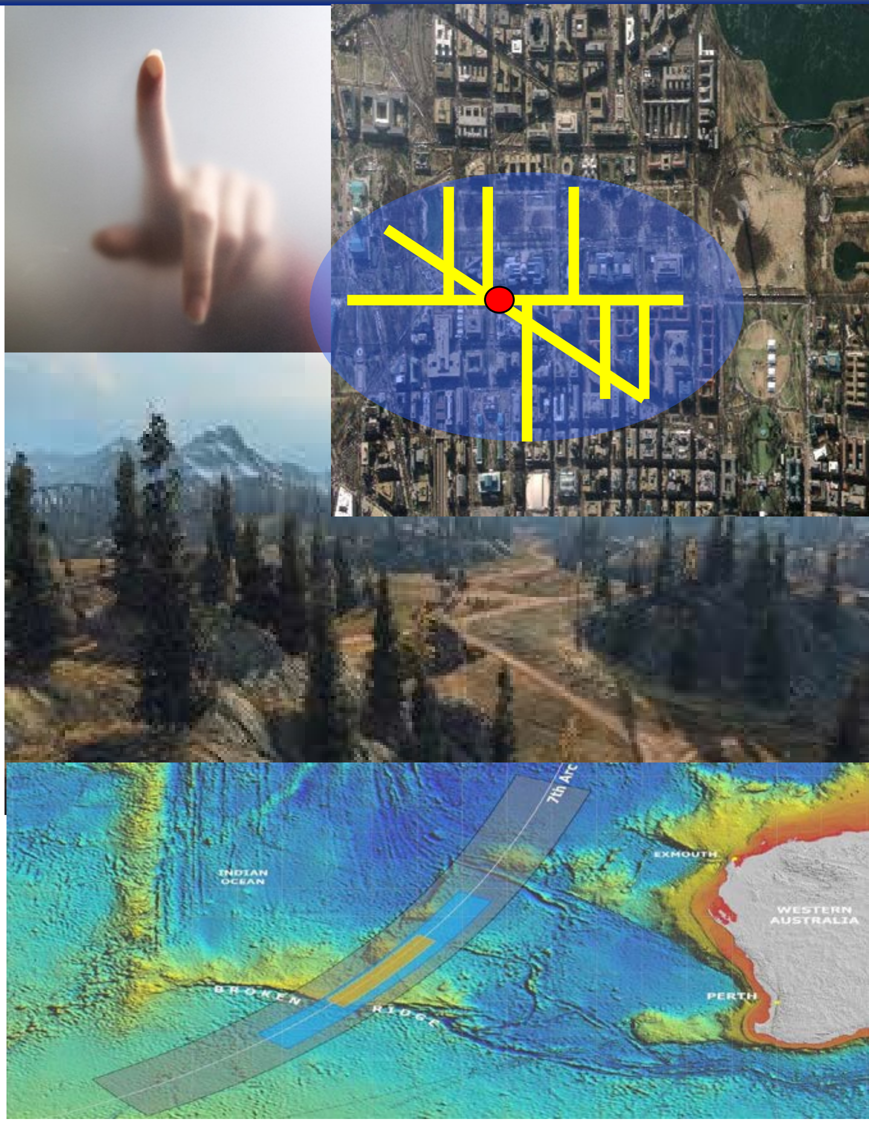
Ellipse Propagation?



Flexible Information Fusion: Estimation Framework Requirements

How can we combine disparate "looks" at a complex and dynamic world into a common operational picture?

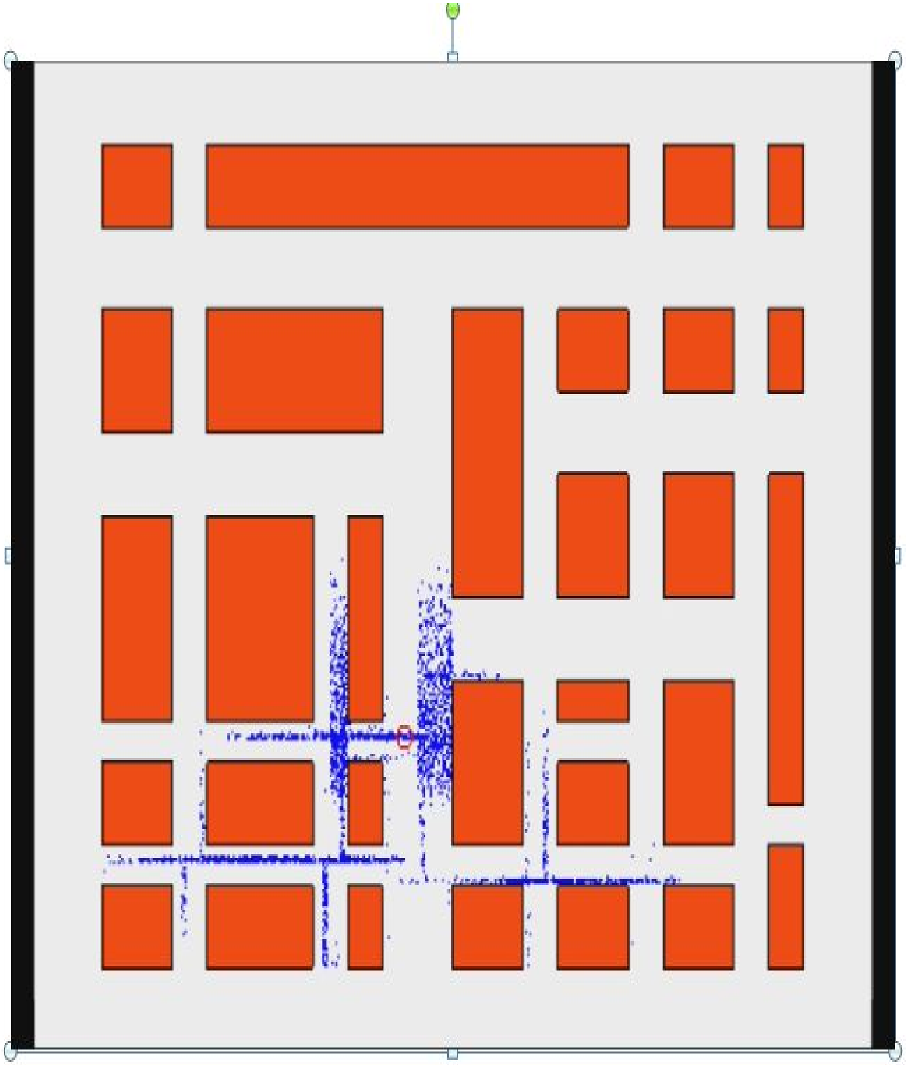
- Must accept widely varying information flow rates that arrive asynchronously and out of sequence
- And provides an arbitrarily rich expression of uncertainty
- While ingesting very non-traditional (negative) perceptions
- And requires a common underlying mathematical framework that is capable of ingesting human-generated information flows



Beyond the Kalman Filter

Traditional approach to estimating battle state (target tracks, blue force tracks, etc.) relies on Kalman Filters

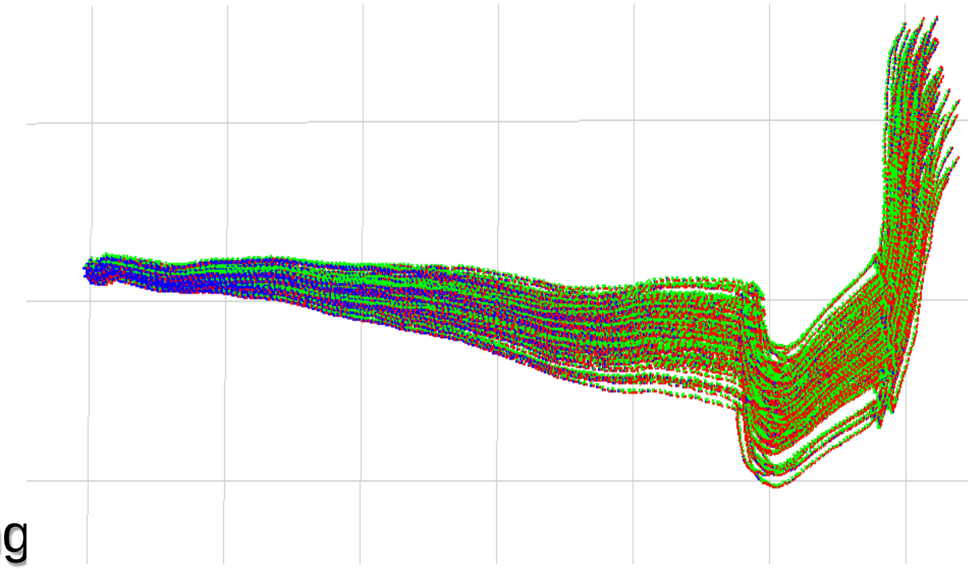
- Cannot express non-Gaussian beliefs
- Can only fuse Gaussian measurements:
  - No logical measurements (e.g. A target is on the house if the lights are on)
  - No negative measurements (GMTI sensor doesn't return an hits in a region of interest)
- We proposed sample-based Bayesian filters as fundamental technology for Perception in Complex and Contested Battle-spaces…

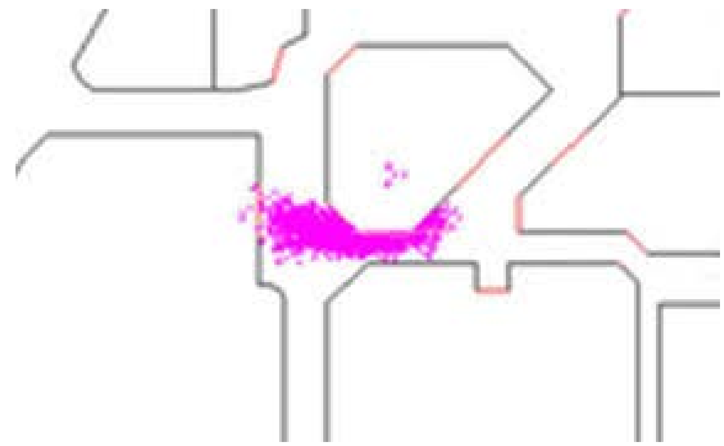


Bayesian Inference in Contested Environments

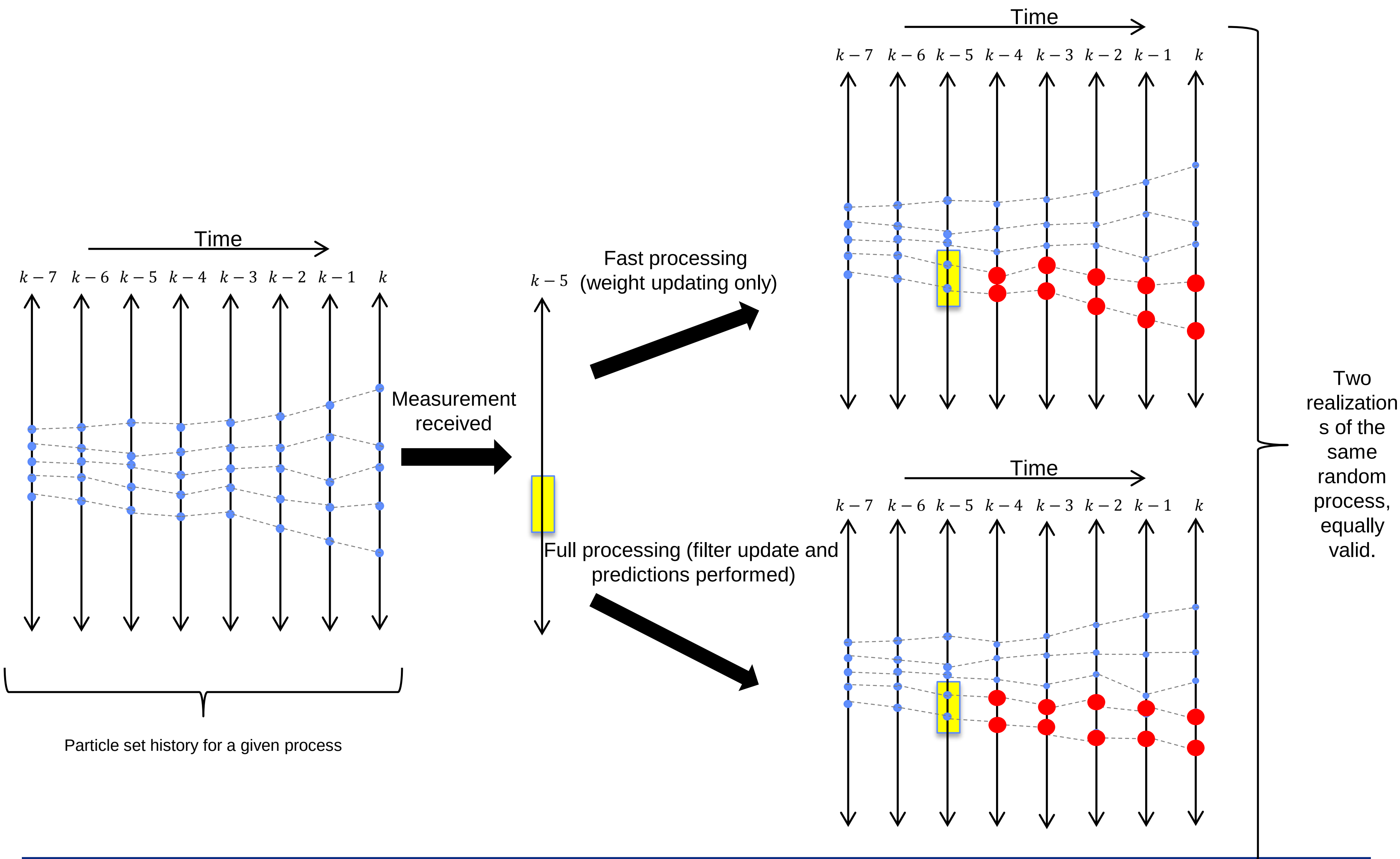
Contested Environments might create false or delayed measurements…

- Fast Out-of-Sequence Particle Filtering technology
  - At the cost of increased memory requirements
- Stored particles allow back-testing measurements for validity
  - Can test whether a particular information source is sending “reliable” data
- Or elegantly removing the effect of previously fused measurements that are now known to be spurious
  - Time required is only linear in the number of particles.





Out-of-Sequence Information



Out of Sequence Information

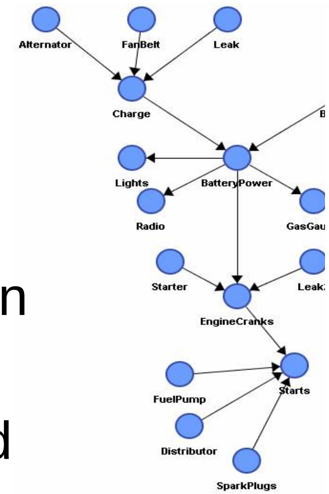
- Problem with Fast Measurement Processing (FDM) approach: **resampling.**
- If a resampling occurs at any time between k_m and k, then FDM cannot work.
- Solution: keep track of the latest resampling time, k_r. If $k_r < k_m$, then it is safe to perform the FDM. Perform the normal (slow) measurement processing otherwise.

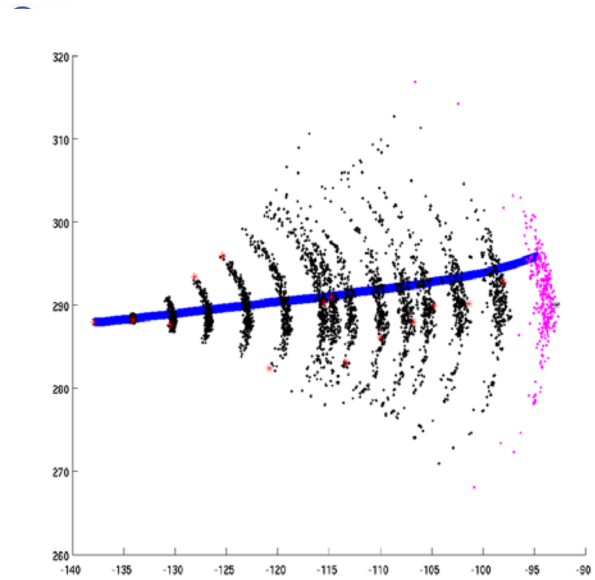
- It can be shown that for our UGS model, the estimator obtained by using this hybrid FDM approach is consistent with a (much slower) brute-force out-of-sequence approach.

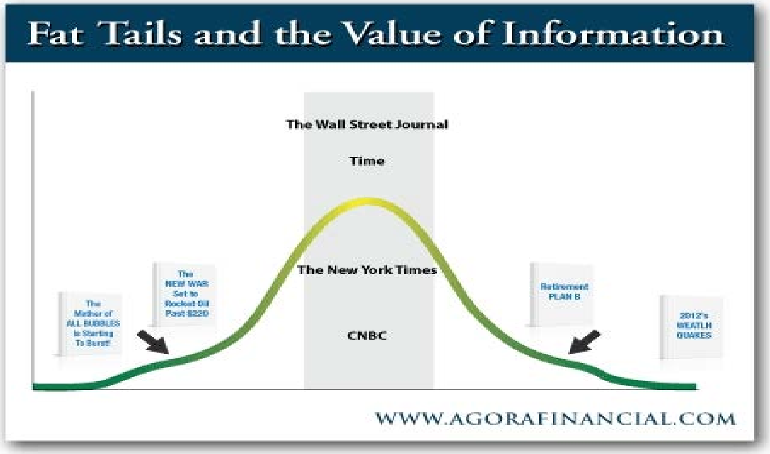
Bayesian Engine: Particle Filters integrated into Belief Network

Our Bayesian engine provides flexible modelling of arbitrarily complex uncertainties:

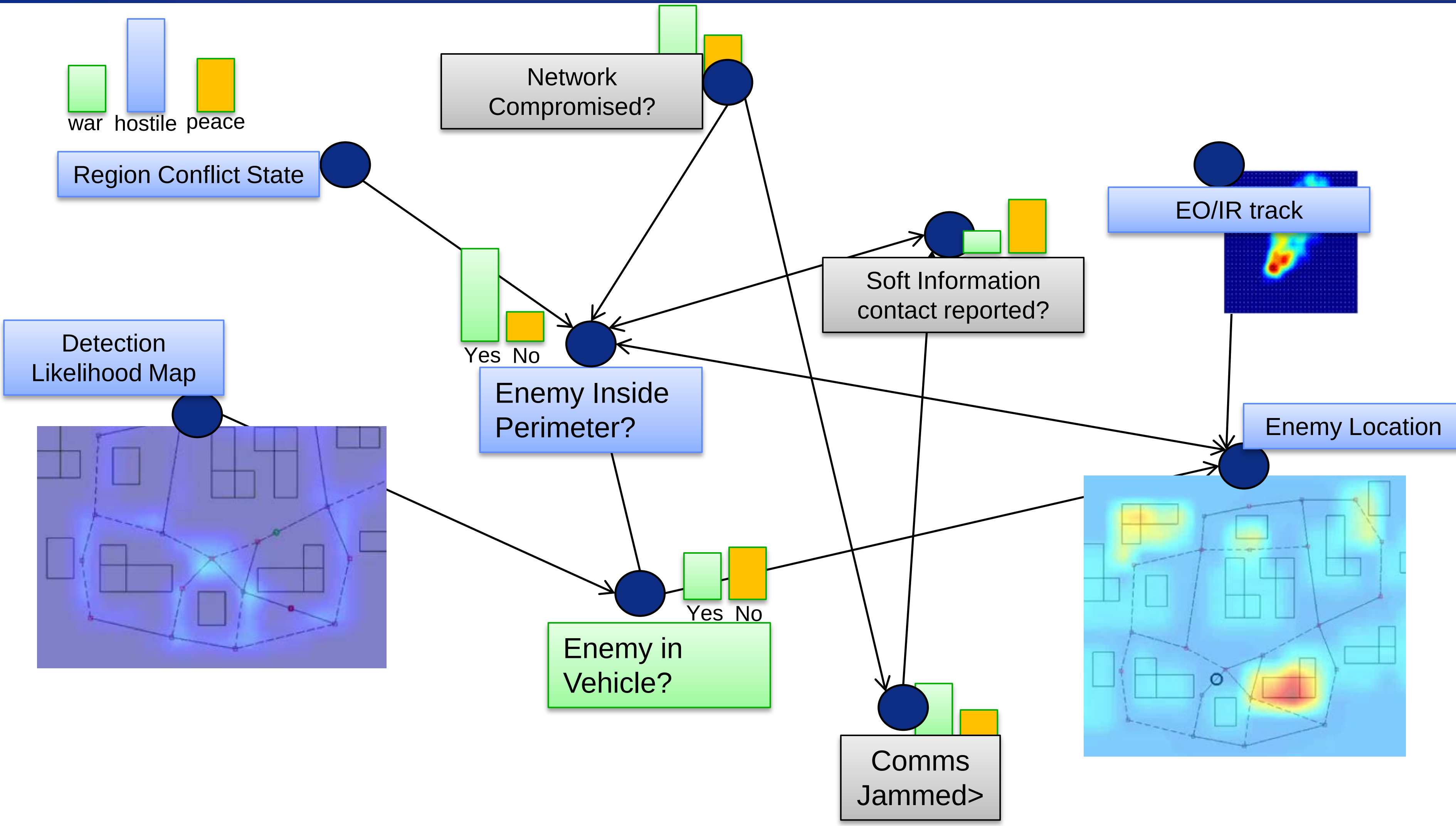
- Can be compressed for communication by marginalization over a set of kernels…
- Allows “negative information” and other unusual measurement modalities
- Allows for computing “Value of Information” via classical decision theory
- And provides hooks for human decision-aiding and risk-aware sensor management.





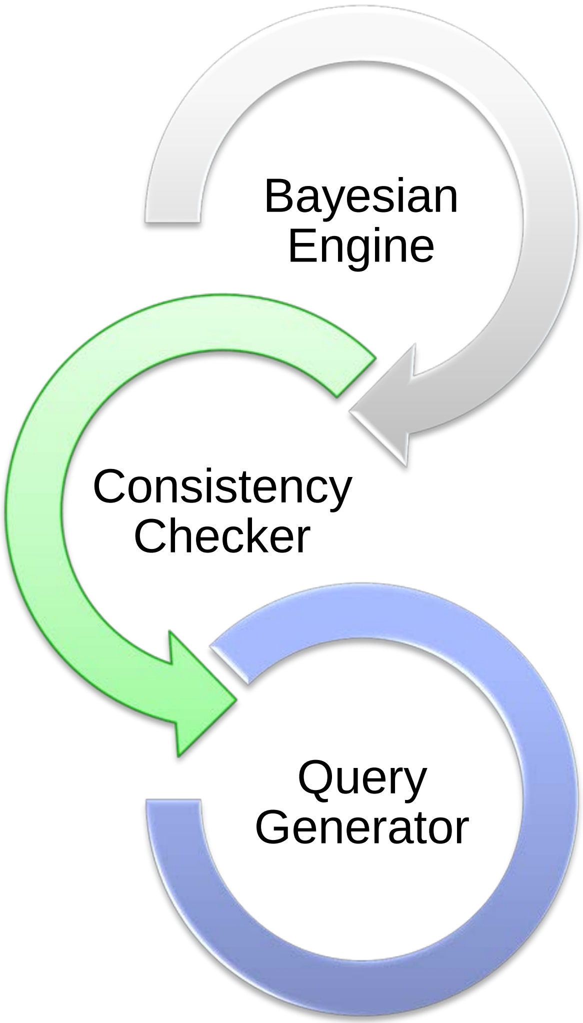


Bayesian Engine Example



Curious Partner

- Even in all-human teams, “getting on the same page” is difficult.
- When Autonomous Systems are participating with other autonomous systems or humans its even more difficult: how can we bridge gap?
- Need method for autonomous system to do two things:
  - Understand when its understanding of the situation has diverged from its teammates’
  - Ask the team a relevant question to bridge the divergent world-view.
- Curious Partner consists of 3 pieces: a Bayesian Engine to model the world, a Consistency Checker algorithm to ascertain whether team members are in sync, and a Query Generator algorithm to ask a good question.



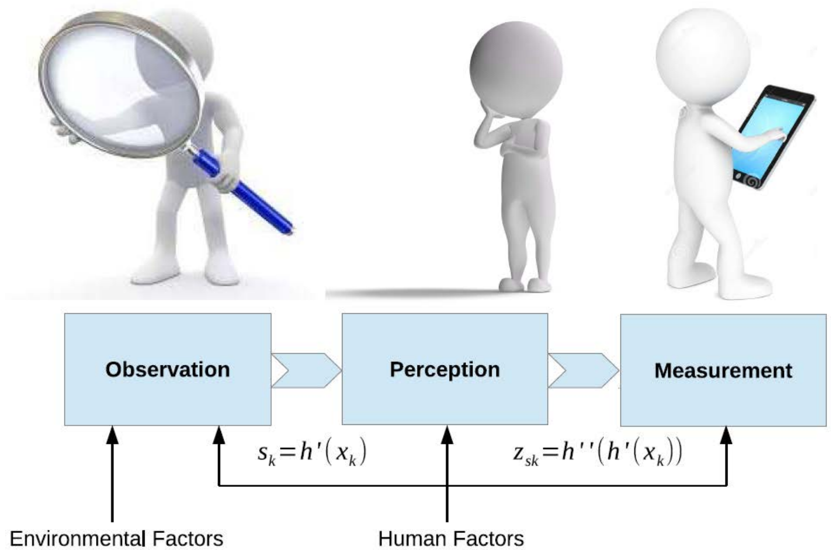
Future Work

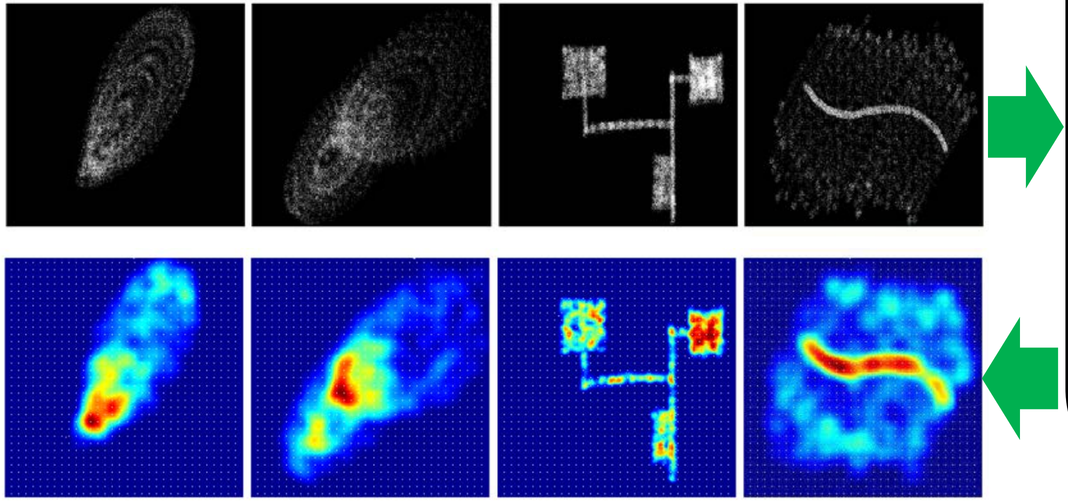
- How can we incorporate knowledge of the evolving network topology to provide implicit measurements to improve Bayesian Engine Situational Awareness?
- How fragile is “Curious Partner” technology to cyber threats or network degradation? How to robustify?
- Intersection of Perception/Decision Making/Cyber/Network Control: Unexplored synergies and potential fragilities!

Touch Interface for Soft Information Modeling

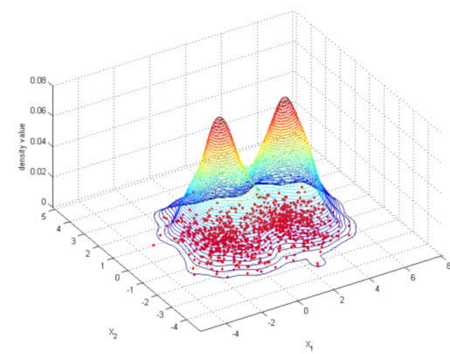
Goal: Develop a human sensor model using touch interface to represent soft information in a mathematical form.

- Natural extension of human perception
- Flexible to encode a large class of information
- Information encoded using single, multiple, and directional finger strokes





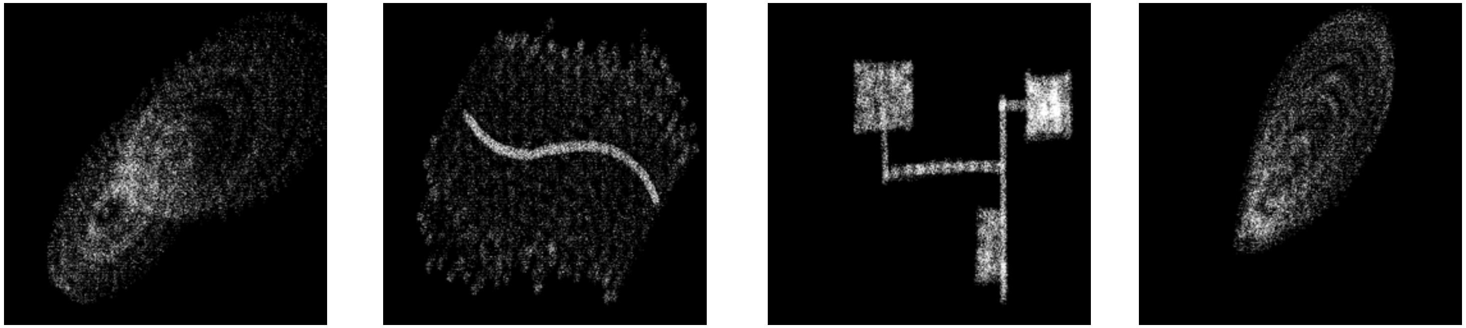
Kernel Density Estimator



$$\hat{p}(\mathbf{z}_{sk}) = \frac{1}{\Gamma}\sum_{i=1}^{\Gamma}\frac{1}{h_1 h_2}\prod_{j=1}^{2}K_j\left(\frac{\mathbf{z}_{sk}-\gamma_i^j}{h_j}\right)$$

Touch Interface for Soft Information Modeling

- Combination of single, multiple, and overlapping strokes
- Flexible and natural medium – *a large class of qualitatively distinct information*
- Robust wrt human variability and requires *no offline training*

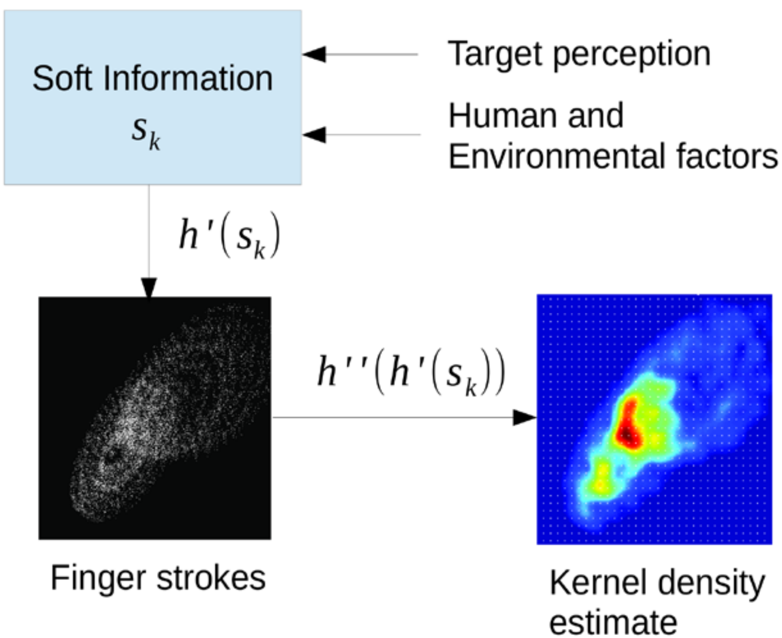


How to obtain a measurement likelihood function from touch data?

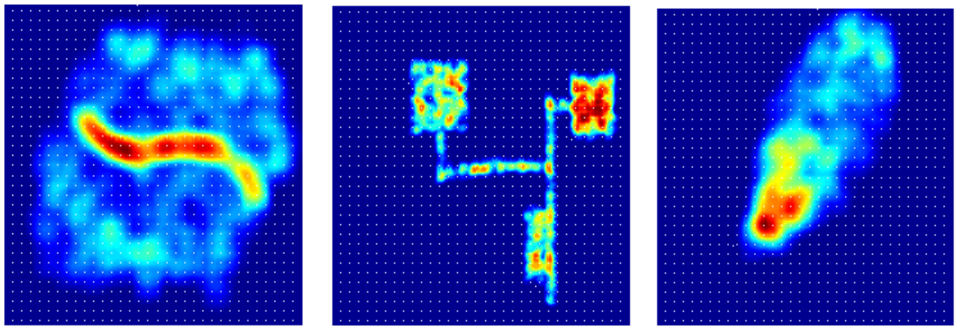
- Soft information - $\mathbf{s}_k = h'(\mathbf{x}_k)$ *perceived information*
  - *Observation to perception*
  - *Socio-temporal variability in* $h'(\mathbf{x}_k)$

Touch Interface for Soft Information Modeling

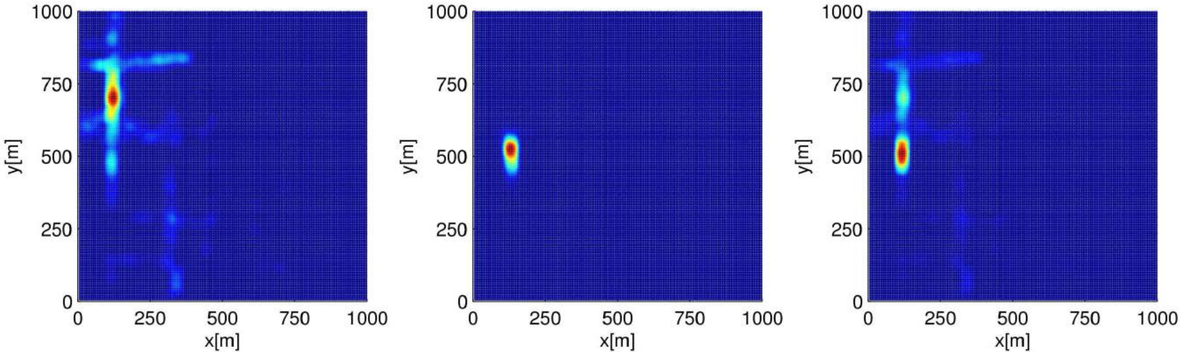
- *Perception to measurement* - $\mathbf{z}_{sk} = h''(\mathbf{s}_k) = h''(h'(\mathbf{x}_k))$
  - *Large uncertainty* – longer strokes, *High confidence* - multiple overlapping strokes, *State gradient* – orientation of strokes, +*ve and –ve information, prior distribution*
- *Measurement likelihood function* – Kernel density estimator



Point cloud to density functions



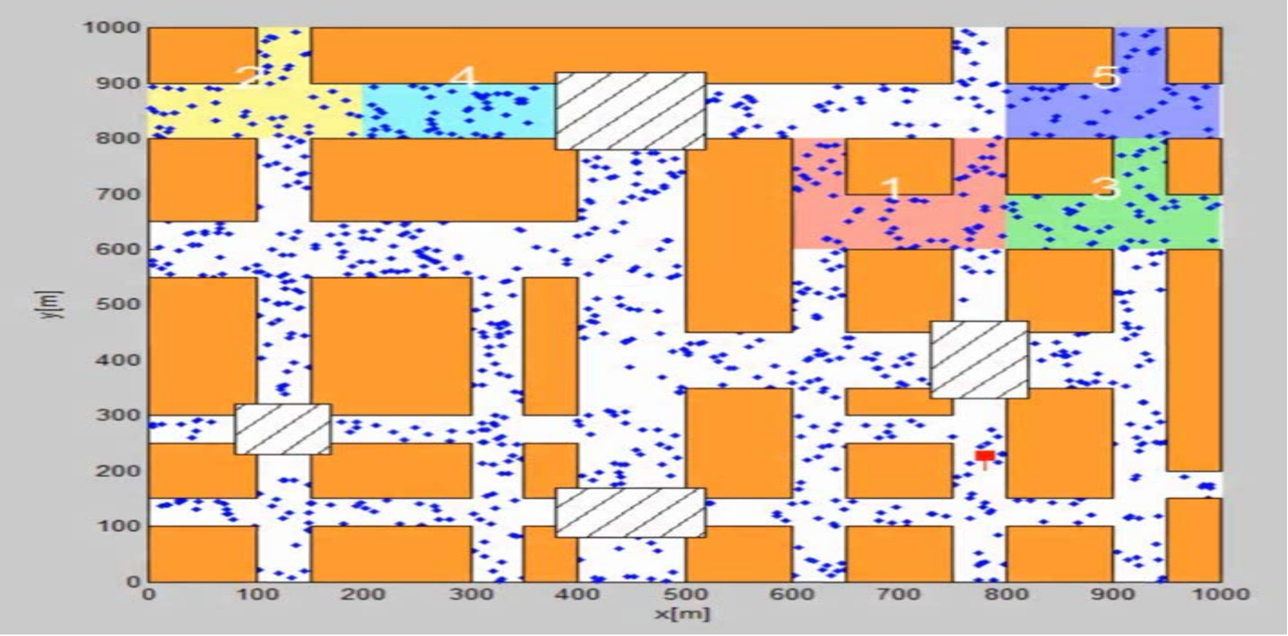
Touch Interface for Soft Information Modeling



Performance w/ Soft Sensing

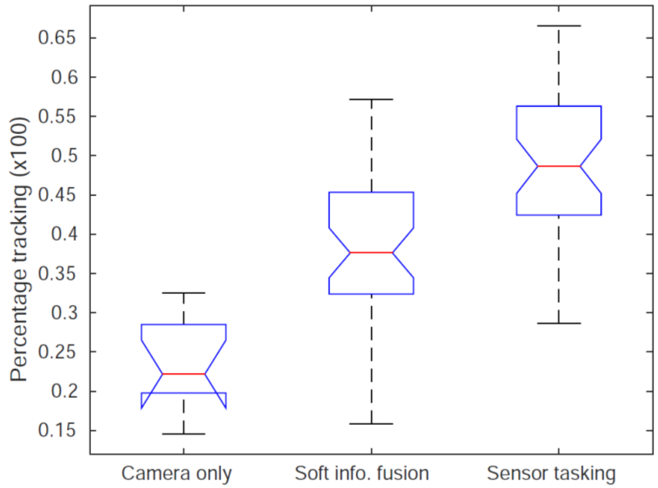
Perc. target detection - 72% ↑
Tracking quality - 10% ↑
Position RMS error - 24% ↓
Position std. dev. - 17% ↓

Urban Target Tracking

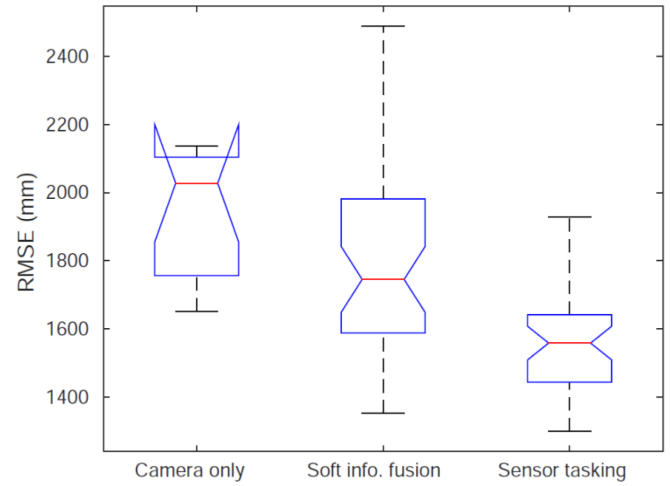


Soft Information Fusion and Sensor Tasking for Urban Target Tracking

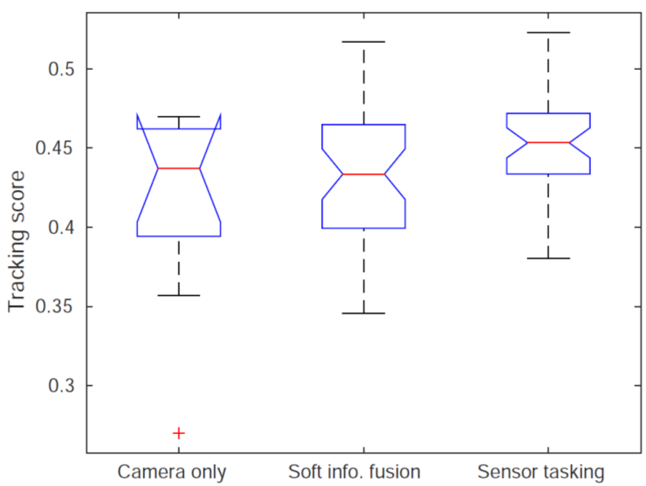
Perc. Target Tracking



RMSE



Tracking score



Percentage target tracking

					p − value
'Sensor tasking'	'Camera'	[0.1816]	[0.2601]	[0.3386]	[9.7812e − 10]
'Sensor tasking'	'Soft info. fusion'	[0.0665]	[0.1158]	[0.1652]	[7.3176e − 07]
'Camera'	'Soft info. fusion'	[−0.2226]	[−0.1443]	[−0.0660]	[9.1576e − 05]

Tracking score

					p − value
'Sensor tasking'	'Camera'	[0.0025]	[0.0377]	[0.0730]	[0.0330]
'Sensor tasking'	'Soft info. fusion'	[0.0020]	[0.0241]	[0.0463]	[0.0296]
'Camera'	'Soft info. fusion'	[−0.0488]	[−0.0136]	[0.0215]	[0.6269]

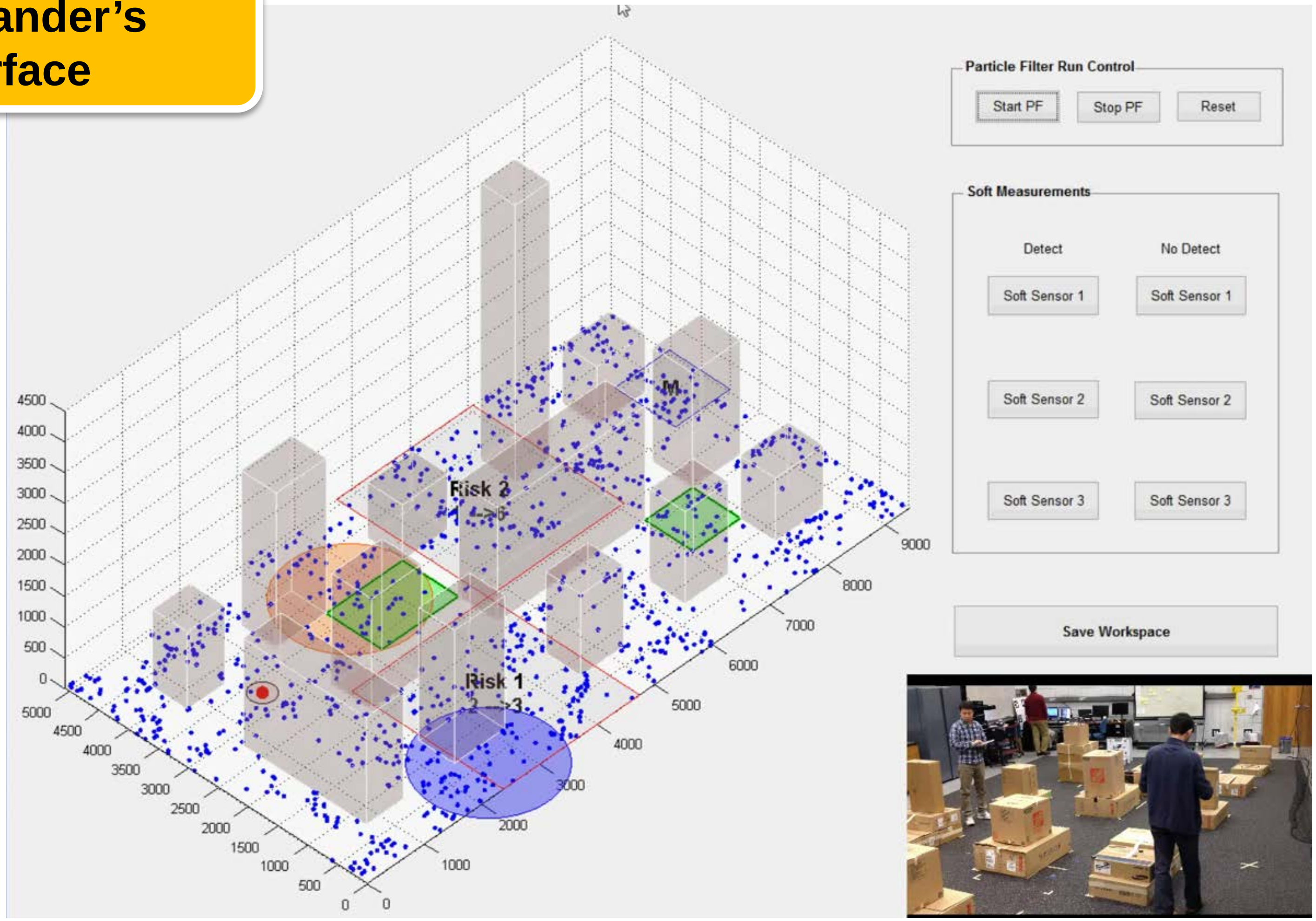
RMSE

					p − value
'Sensor tasking'	'Camera'	[−569.4858]	[−396.9495]	[−224.4131]	[1.1325e − 06]
'Sensor tasking'	'Soft info. fusion'	[−336.0175]	[−227.5634]	[−119.1092]	[8.4639e − 06]
'Camera'	'Soft info. fusion'	[−2.7289]	[169.3861]	[341.5011]	[0.0547]

AIAA, GNC Conference 2012. Journal submission in preparation.

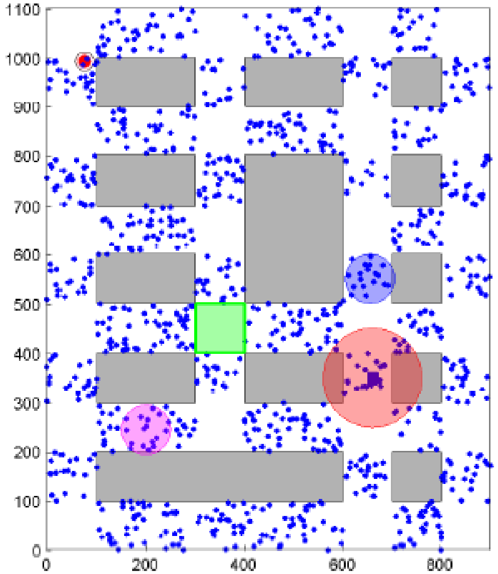
Soft Information Fusion and Sensor Tasking for Urban Target Tracking

Commander's Interface

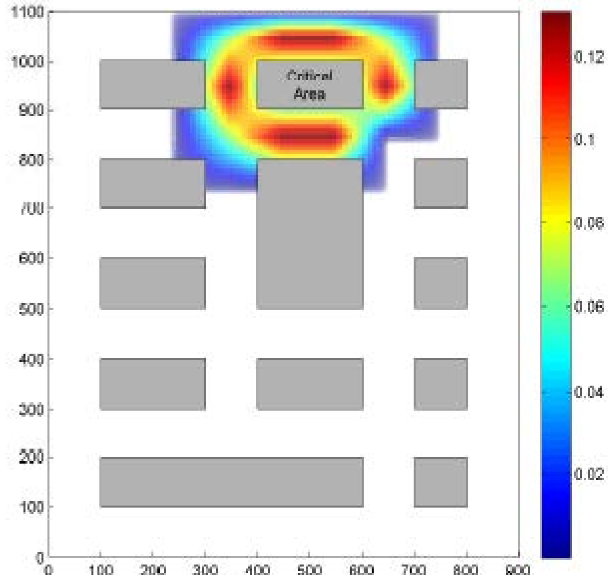


Mutual Information based Risk-aware Active Sensing

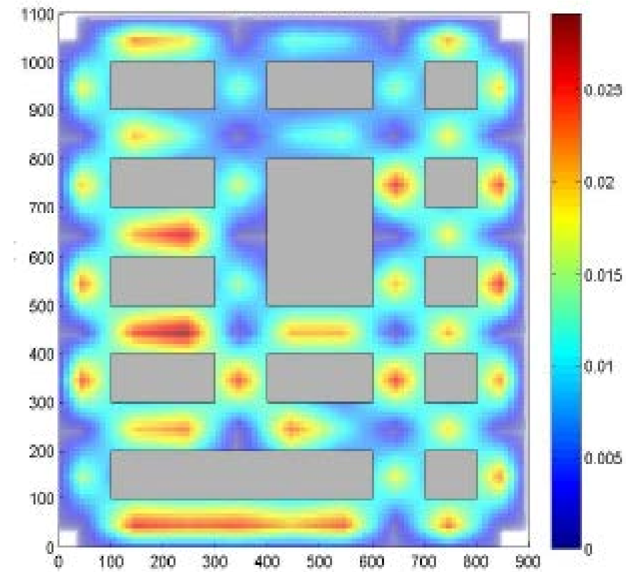
Target State Belief Map



Hazard Map

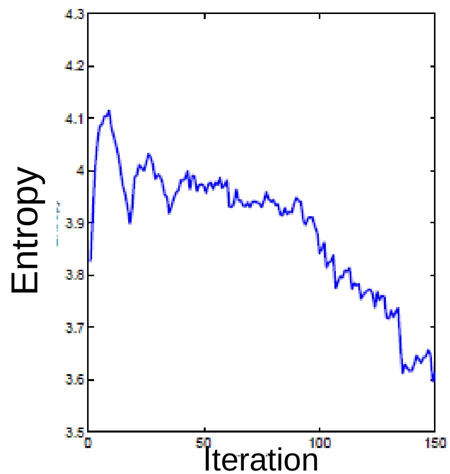


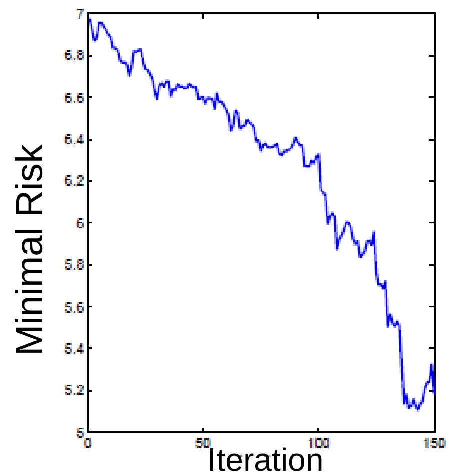
Risk Map



- Average Reduction of Estimate Entropy is 54%
- Average Reduction of Risk Value is 43%

Accepted by Systems, Man, and Cybernetics, 2015.



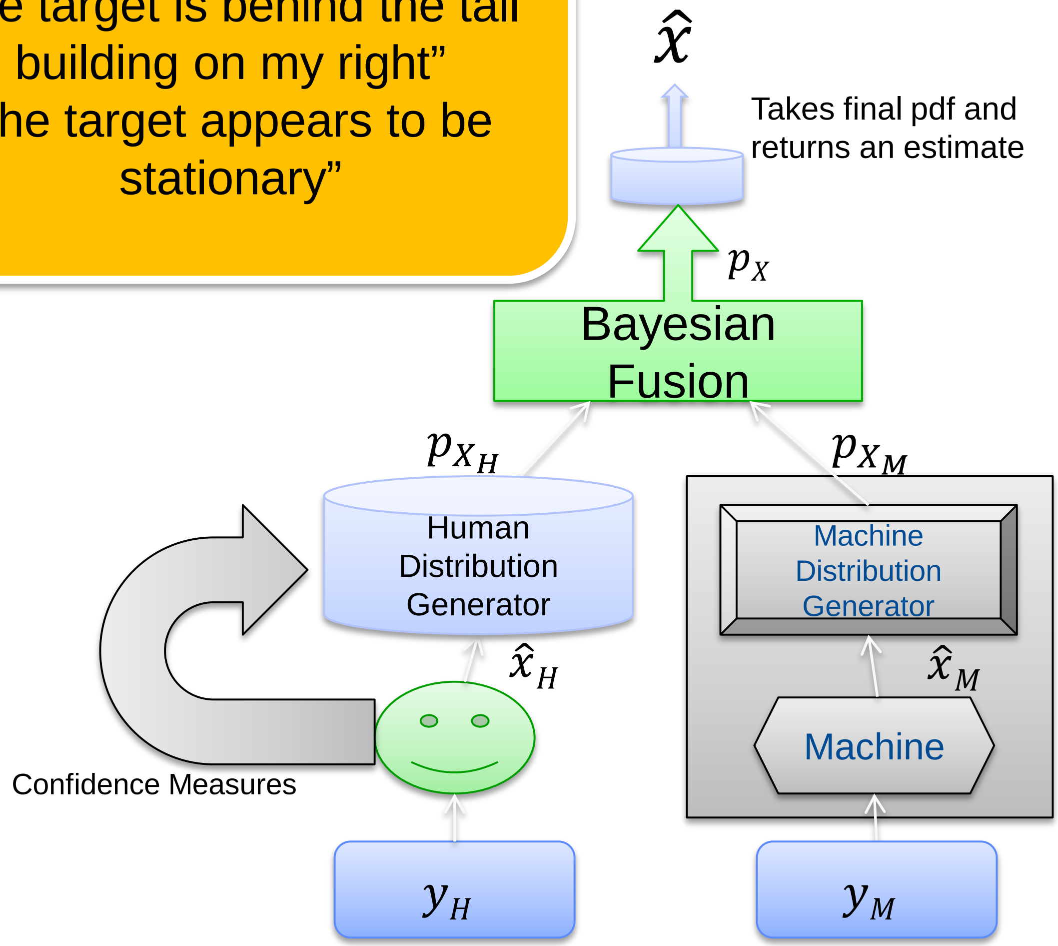


Soft Information Fusion

Humans are Sensors:

- Provide "Soft information" – *qualitative or categorical*
  - Voice, text, or user-interface derived signals
- Previous work was rigid in how human perceptions could be incorporated:
  - Limited vocabulary/codebook
  - Softmax models
- State of the art didn't model human physiological issues well
  - *Training level*
  - *Alertness/fatigue*
  - *Stress …*

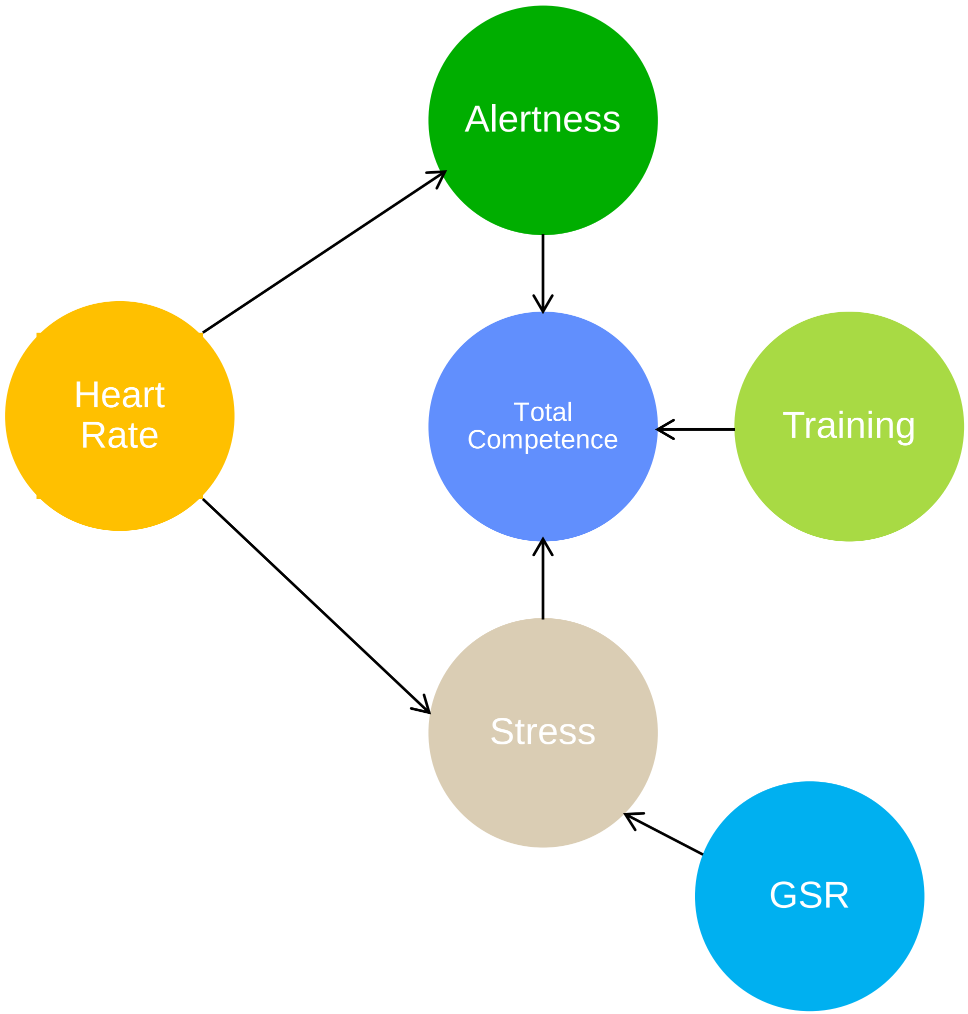
"the target is behind the tall building on my right"
"the target appears to be stationary"



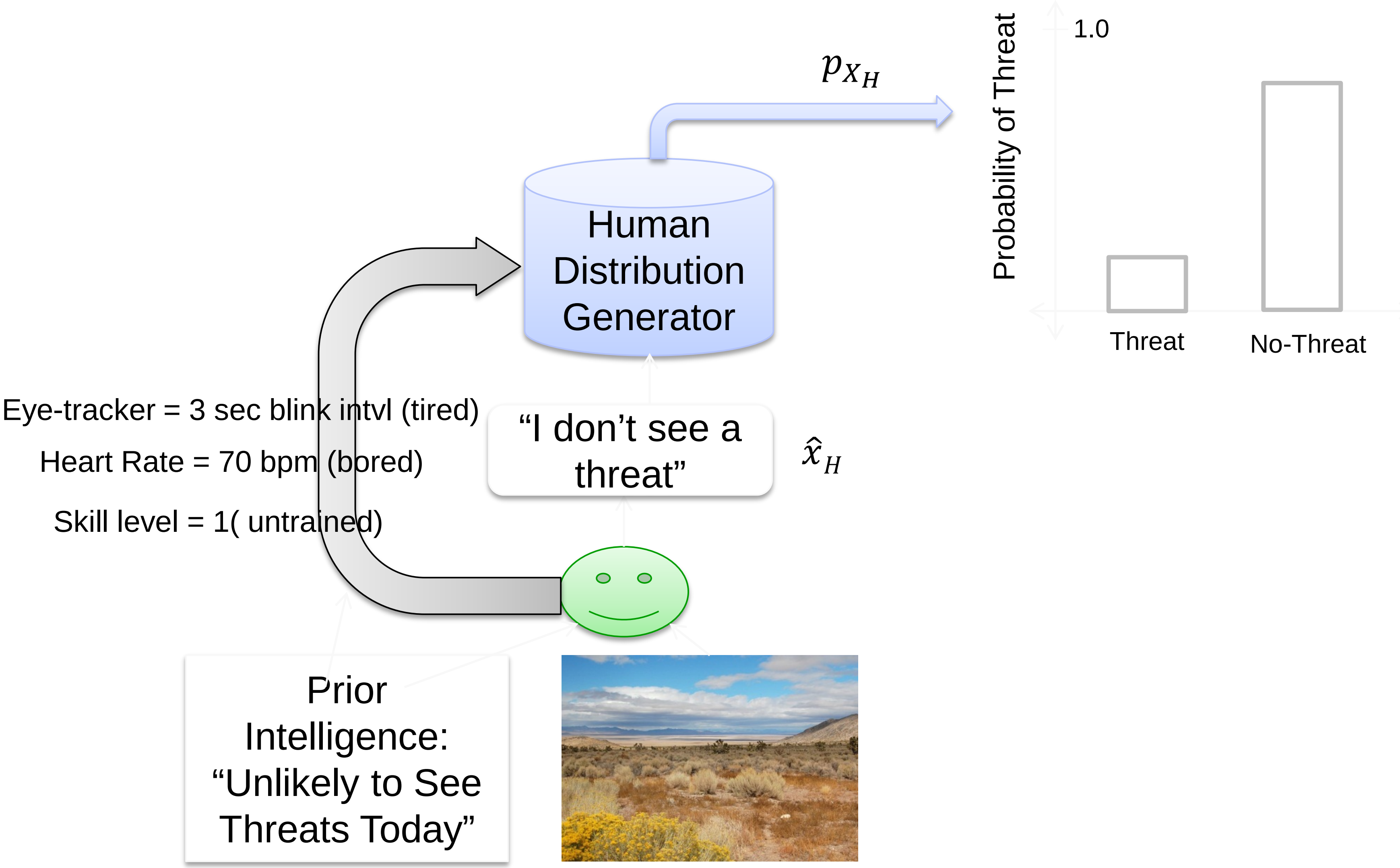
Model Human (Sensor) Performance with BBN

Bayesian Belief Network for Human Performance as a Soft Sensor:

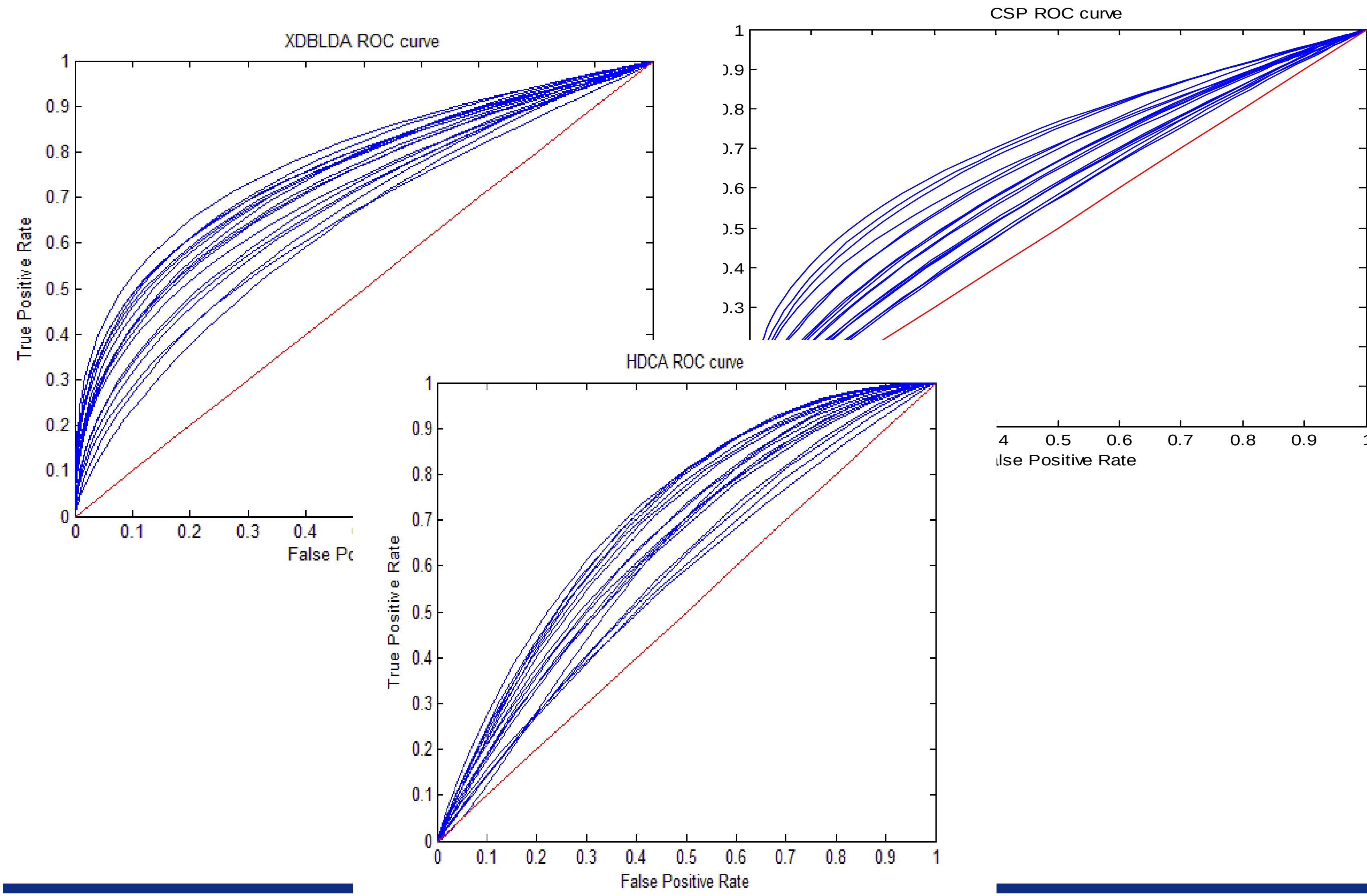
- Uses variety of input data:
  - *Heart Rate*
  - *Galvanic Skin Response*
  - *Training logs or aptitude tests*
  - *Eye Tracker*
  - *EEG*
- Total Competence is probability distribution over several classes:
  - *Very High, High, Medium, Mediocre, Poor*
  - *Used to modify human's soft "reports"*
  - *Individualizable!*



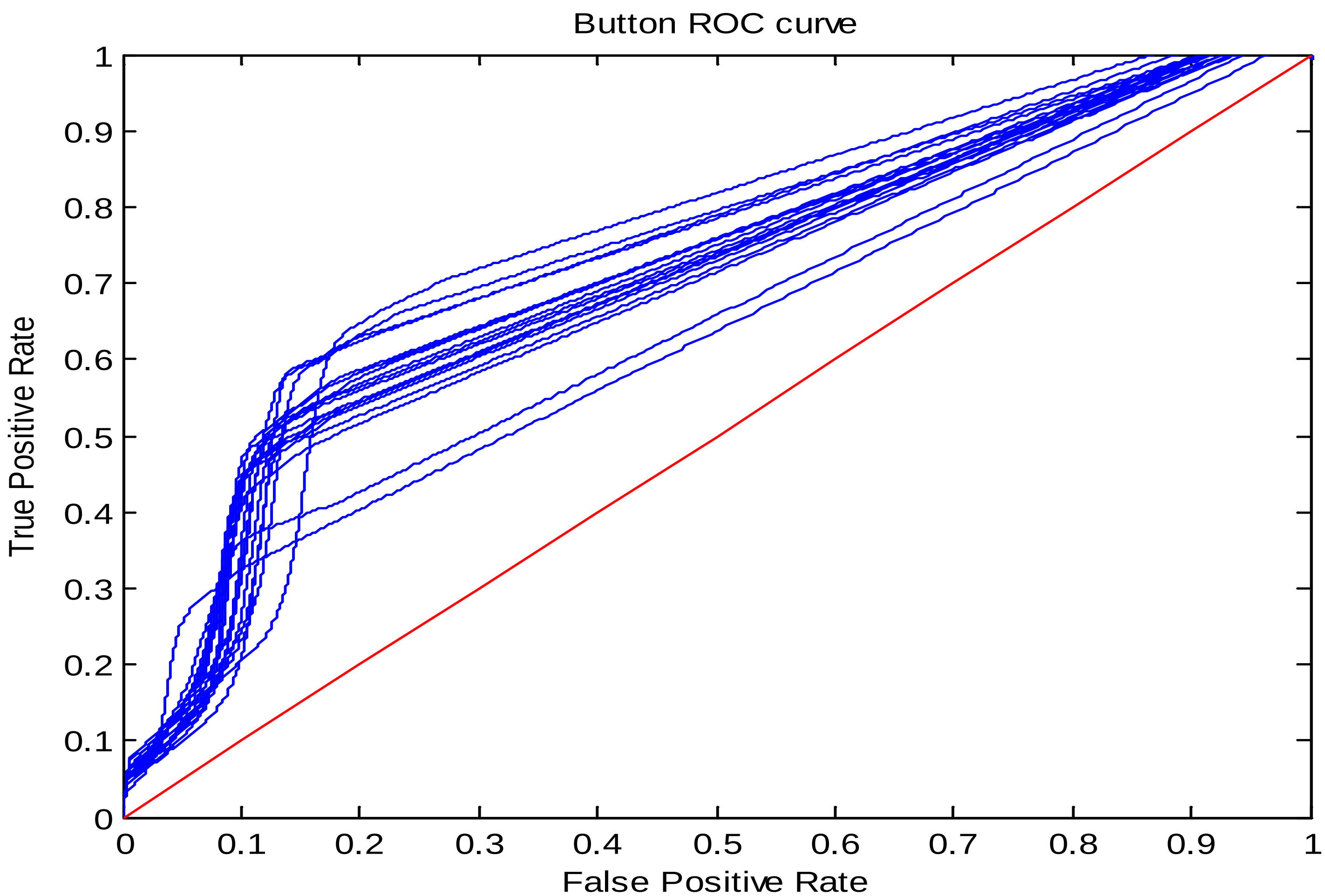
Human Sensor with Uncertainty



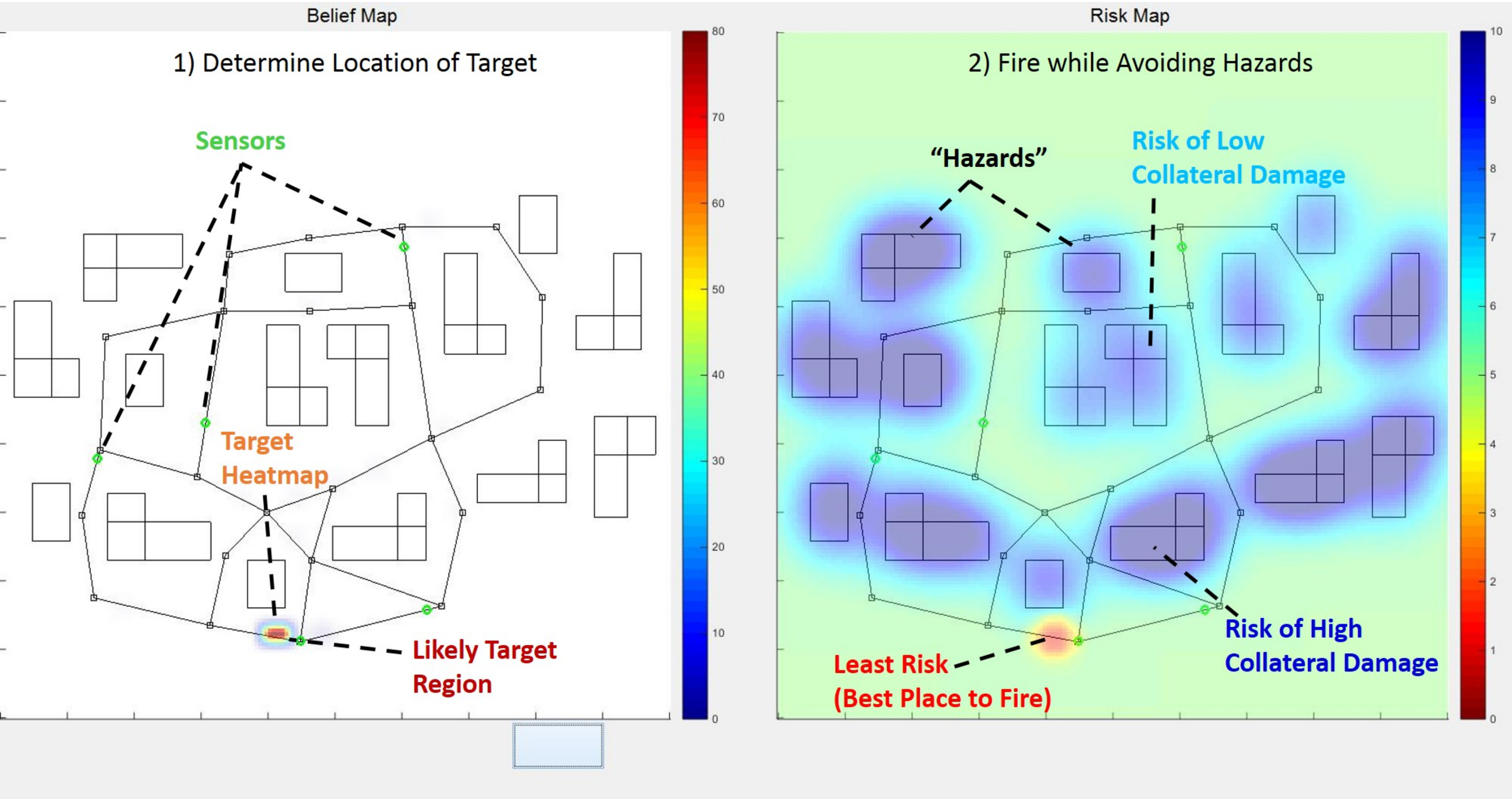
Individualized Likelihoods …



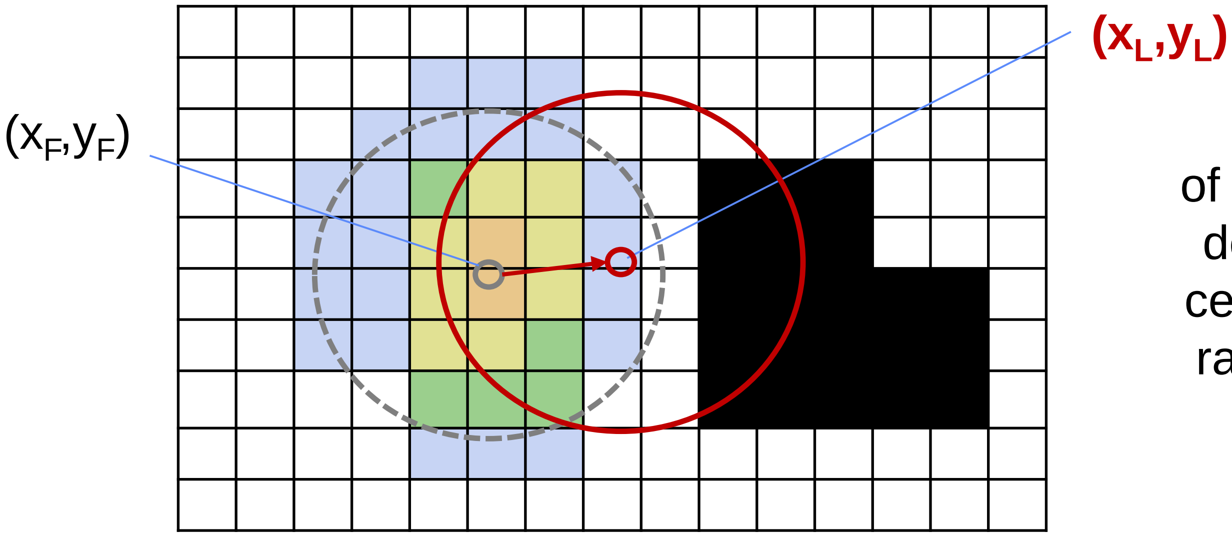
Button Press Likelihoods



Decision Support Interface



Expected Risk Calculation



The center (x_L,y_L) of the actual blast radius will deviate from the indended center (x_F,y_F) according to a random normal distribution with SD=0.25*r

Probability of hitting target given fire at (x_F,y_F)

Sum over entire grid

Probability that target is at (x_i,y_j)

Probability that blast radius contains (x_i,y_j) given fire at (x_F,y_F)

$$P(h|x_F,y_F) = \sum_{i,j=1}^{M,N} P(h|x_i,y_j)P(x_i,y_j|x_F,y_F)$$

Expected Risk Calculation

Probability of damaging (x_i,y_j) given fire at (x_F,y_F)

Probability of damage at (x_i,y_j) given blast radius contains it

Probability that blast radius contains (x_i,y_j) given fire at (x_F,y_F)

$$P(d_{i,j}|x_F,y_F) = 1 * P(x_i,y_j|x_F,y_F)$$

Expected Loss given fire at (x_F,y_F)

Expected total damage

Expected reward

$$E[R(x_F,y_F)] = \sum_{i,j=1}^{M,N}\{d_{i,j} \cdot P(d_{i,j}|x_F,y_F)\} - r_h \cdot P(h|x_F,y_F)$$

Damage at (x_i,y_j)

Reward for hitting target