Flexible Human-Machine Information Fusion and Perception in Contested Environments

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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

Particle set history for a given process

Measurement received

Fast processing (weight updating only)

Full processing (filter update and predictions performed)

Two realizations of the same random process, equally valid.
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.
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

Detection Likelihood Map

Region Conflict State

Network Compromised?

Enemy Inside Perimeter?

Soft Information contact reported?

Enemy in Vehicle?

Comms Jammed>

EO/IR track

Enemy Location

war hostile peace
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!
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
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 - \( s_k = h' (x_k) \) *perceived information*
  - Observation to perception
  - Socio-temporal variability in \( h' (x_k) \)
• **Perception to measurement** - $z_{sk} = h''(s_k) = h''(h'(x_k))$
  
  - 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

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**Diagram:**

- **Soft Information** $s_k$
- **Target perception**
  - Human and Environmental factors
  - $h'(s_k)$
- **Three steps**:
  1. Finger strokes
  2. $h'(s_k)$
  3. $h''(h'(s_k))$
- **Output**: Kernel density estimate

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**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% ↓
Soft Information Fusion and Sensor Tasking for Urban Target Tracking

Commander’s Interface
Mutual Information based Risk-aware Active Sensing

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

Accepted by Systems, Man, and Cybernetics, 2015.
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”
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**

**Human Distribution Generator**

- **Heart Rate**: 70 bpm (bored)
- **Eye-tracker**: 3 sec blink intvl (tired)
- **Skill level**: 1 (untrained)

**Prior Intelligence**: “Unlikely to See Threats Today”

**Probability of Threat**

- **$p_{X_H}$**
- **$\hat{x}_H$**

**“I don’t see a threat”**

Eye-tracker = 3 sec blink intvl (tired)
Heart Rate = 70 bpm (bored)
Skill level = 1 (untrained)
Individualized Likelihoods …

![XDBLDA ROC curve](image1)
![CSP ROC curve](image2)
![HDCA ROC curve](image3)
Button Press Likelihoods

Button ROC curve

True Positive Rate vs. False Positive Rate
Decision Support Interface

1) Determine Location of Target

- Sensors
- Target Heatmap
- Likely Target Region

2) Fire while Avoiding Hazards

- “Hazards”
- Risk of Low Collateral Damage
- Least Risk (Best Place to Fire)
- Risk of High Collateral Damage
Expected Risk Calculation

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

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

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

\[
P(d_{i,j} | x_F, y_F) = 1 \cdot P(x_i, y_j | x_F, y_F)
\]

Expected Loss given fire at \((x_F,y_F)\)

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

Damage at \((x_i,y_j)\)

Reward for hitting target

Expected total damage

Expected reward