

Automated Risk Assessment of Sensor Information Disclosure in Coalition Operations

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Background:

- Mechanical Engineering (B.Sc, M.Sc.)
 - Automatic Control Systems and Computation Fluid Dynamics
- Computer Science (M.Sc., Ph.D.)
 - Machine Learning, Computer Security and Complex Networks

Current Affiliations

- Research Scientist at IHMC
- Graduate Faculty at the Florida Institute of Technology
- Faculty Member at the Center for Applied Optimization (University of Florida)

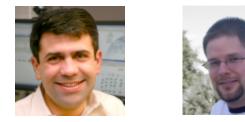
Current Areas of Research

- Cyber Security and Bio-Inspired Resilience
- Critical Infrastructure Protection
- Complex Networks and Distributed Systems
 - Tactical Communication Networks
 - Self-Similarity in Complex Networks
 - Social Network Analysis and Virtual Worlds



Research Team in Ocala, FL

- Marco Carvalho
- Adrian Granados
- Carlos Perez
- Marco Arguedas
- Massimiliano Marcon
- Giacomo Benincasa
- Graduate Students and collaborators
 - UF (Mechanical and Aerospace Engineering, Industrial Engineering, and Computer Science)
 - UF Center for Applied Optimization (Gainesville, FL)
 - Harris Center for Information Assurance (Melbourne, FL)









What is the Problem?

- A sensor network is deployed in an area of interest
- Sensors have different security classifications, or classified capabilities
- The Problem: How to provide information to friends (troops and coalition partners) while minimizing the risk of disclosing the presence and/or location of the classified sensors?

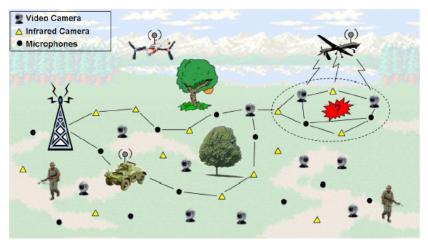


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Related Work

Statistics:

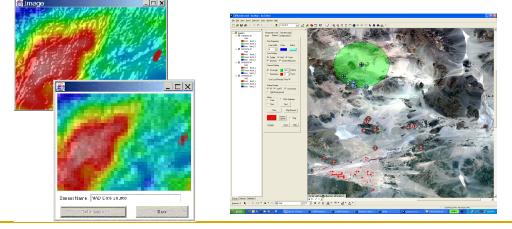
- Statistical Disclosure Control (SDC)
- Statistical Disclosure Limitation (SDL)
- Inference Control
- Data Mining
 - Privacy Preserving Data Mining (PPDM)



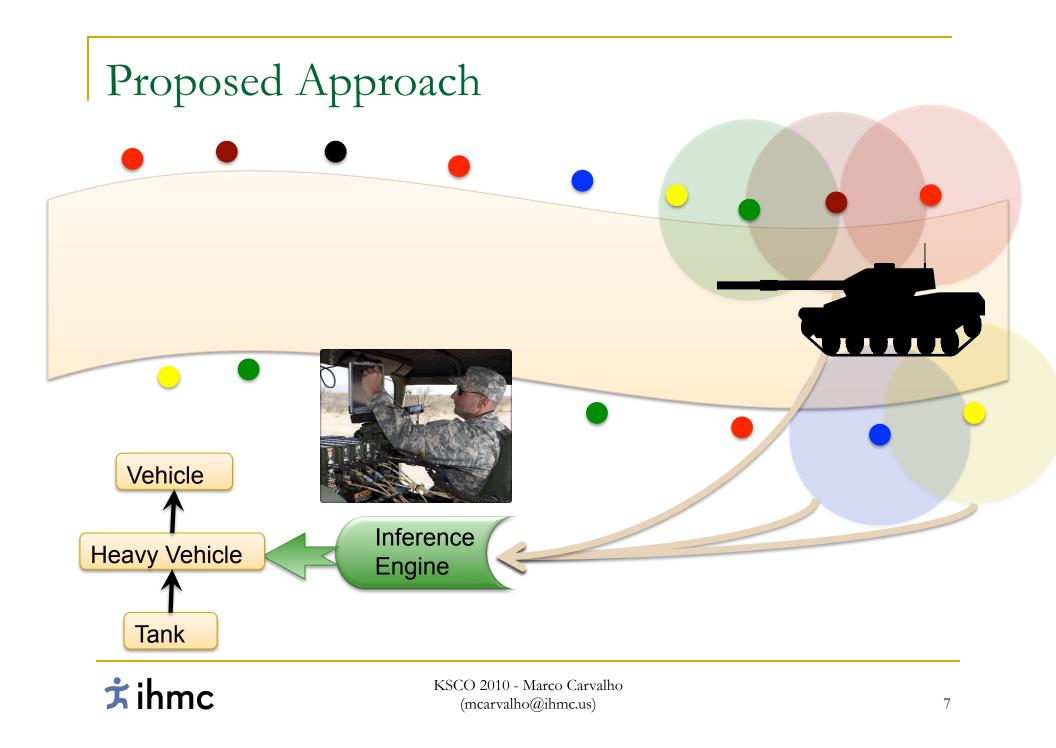
Related Work (cont.)

ARL Collaborative Technology Alliance

- Advanced Decision Architectures
 - Policy-governed information exchange
- Information and Sensor Capability Protection
 - Coalition Operations
 - Adversaries in the field, etc.
 - Risk-adaptive access control



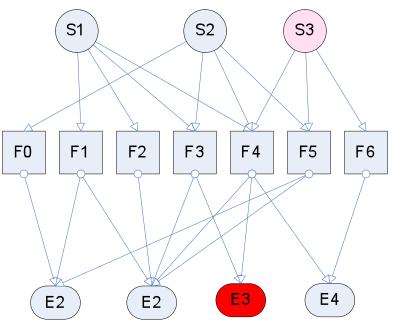




A Simple Example

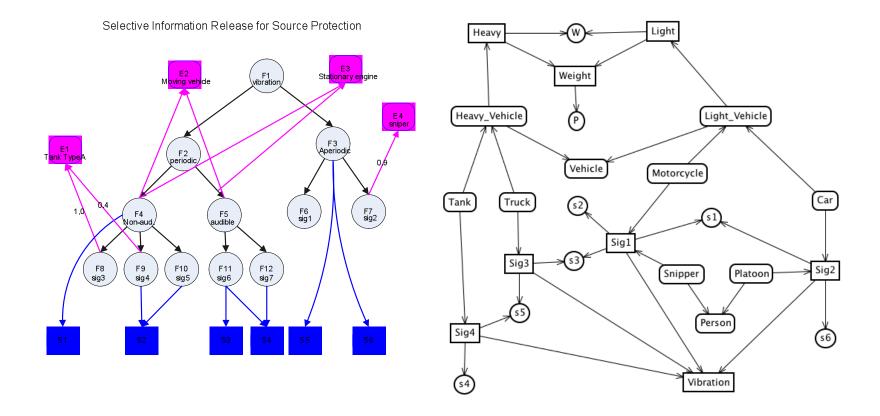
Reporting E3

- Ambiguous sources "S2" or "S3"
- Depending on history of entities previously reported to that soldier, the probability of choosing "S2" is greater than that of choosing "S3"
- Direct Bayesian inference from the soldier side can be used to estimate the presence of sensor "S3"





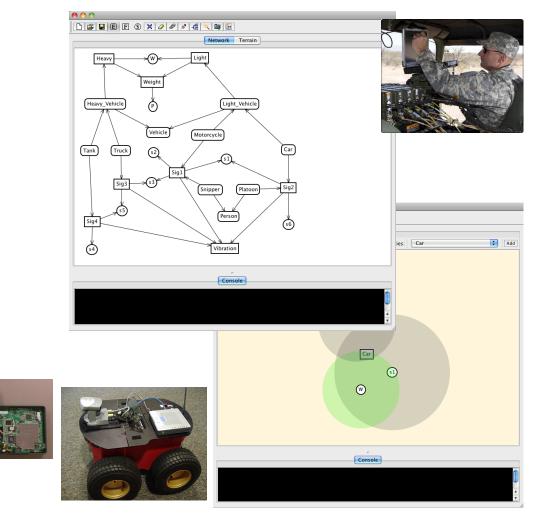
A More Complex Scenario





Proposed Solution

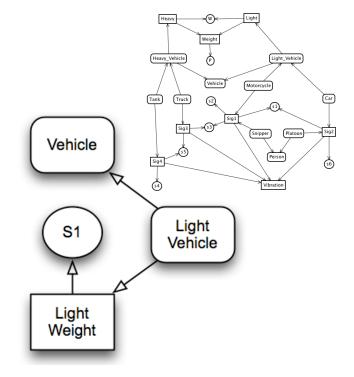
- Build an Automatic Source Protection Network (ASPNet), a Bayesian Network that uses an ontology to represent a hierarchy of entities and features
- Use the ASPNet for detecting entities and for assessing the risk of disclosing sensor information using probabilistic inference





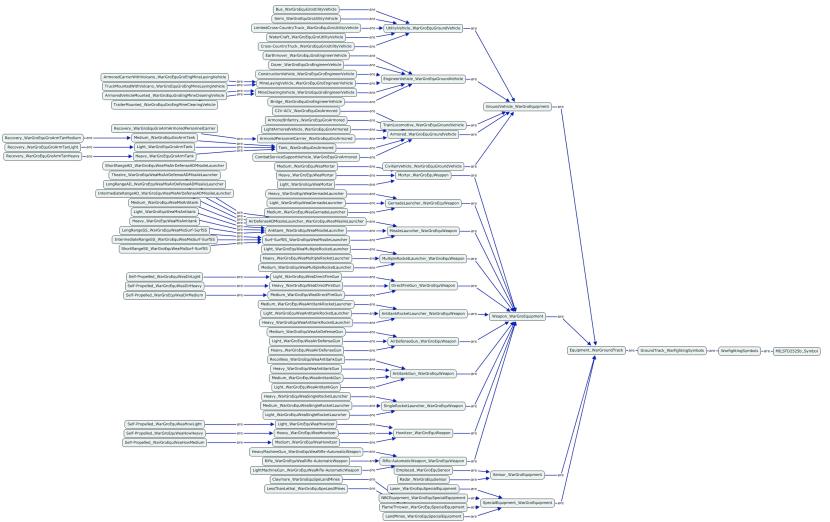
ASPNet Specification

- Bayesian Network
 - Automatically-detected sensor field information, hierarchy of equipment (ontology), and technical database of features and known signatures
- Contains three types of nodes:
 - Entities
 - Features
 - Sensors
- All nodes are binary (true or false)
- Allowed Links:
 - Entities \rightarrow Parent Entities
 - Entities \rightarrow Features
 - Features \rightarrow Parent Features
 - Features \rightarrow Sensors



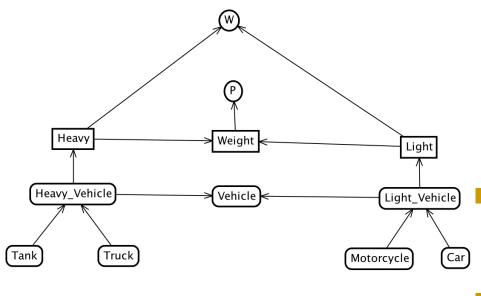


Equipment (Entity) Ontology





ASPNet Example



 Entities: Vehicle, Heavy_Vehicle, Tank, Truck, Light_Vehicle, Motorcycle, Car
 Features: Weight, Heavy, Light
 Sensors: W, P

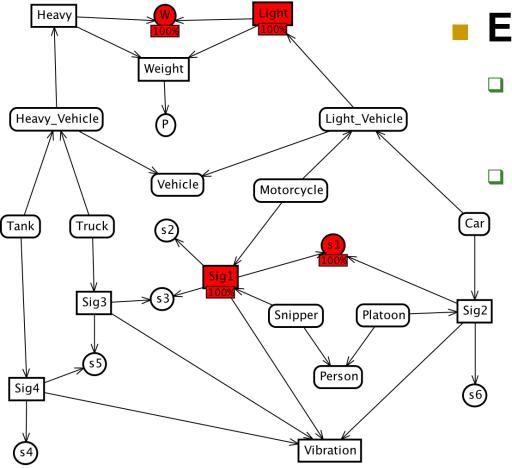


Detecting an Entity

- Gather information provided by the sensors
- Feed that information to the Bayesian Network
- Run an inference algorithm over the network
- Pick the entity or entities with highest probability



Detection Example

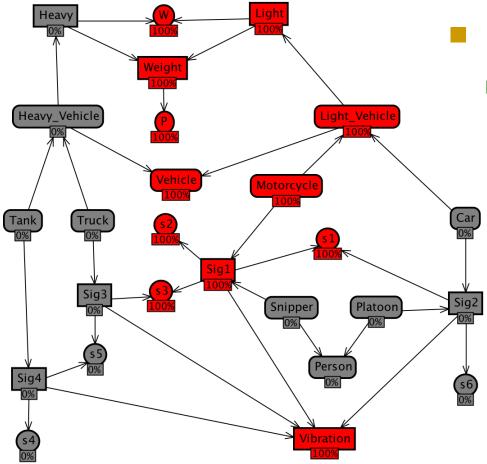


Evidence

- W sensor measured feature Light
- s1 sensor measured
 feature Sig1



Detection Example (continued)



Results of Inference:

- □ The entity is:
 - Vehicle
 - Light_Vehicle
 - Motorcycle



Source Protection Problem

- In the previous example we could disclose to the soldiers that entity is a Motorcycle, a Light_Vehicle or simply a Vehicle
- However, from a sensor protection perspective, there is a different risk for each one of these disclosures



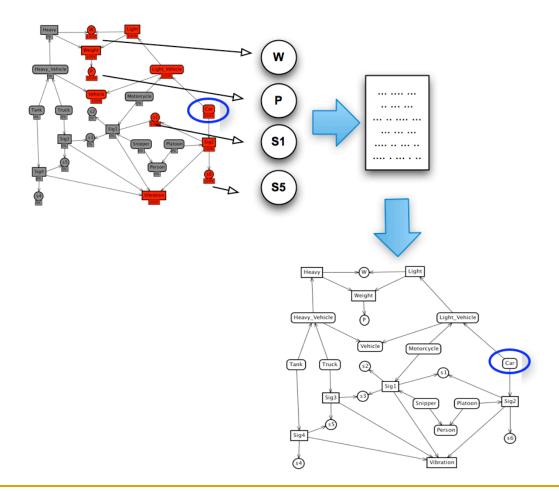
Risk of Disclosing a Sensor

```
Input: N (ASP Network)
Input: e (Entity to be disclosed)
Input: t (Activation threshold)
P \leftarrow \text{DoInference}(N, \{e = true\});
F \leftarrow \{f | f \in N \land \mathbf{IsFeature}(f) \land P(f) > t\};
S \leftarrow \{s | s \in N \land \mathbf{IsSensor}(s) \land \exists f \in F [\mathbf{DetectsFeature}(s, f_i)]\};
F_s \leftarrow \{f | f \in F \land s \in S \land \mathbf{DetectsFeature}(s, f)\};
R \leftarrow \{\};
for C \in \mathcal{P}(S) do
     indexes[1 \dots |C|] \leftarrow 0;
     i \leftarrow 0;
     while C \notin R \land i \ge 1 do
          s \leftarrow C(i);
          indexes[i] \leftarrow indexes[i] + 1;
          if indexes[i] \ge |F_s| then
                indexes[i] \leftarrow 0;
               i \leftarrow i - 1;
          else
                if i = |C| then
                      E \leftarrow \{\};
                      for j \in \{1 ... |C|\} do
                          s \leftarrow C(j);
                          E \leftarrow E \bigcup F_s[indexes[j]];
                     end
                     P \leftarrow \mathbf{DoInference}(N, E);
                     if P(e) \ge t then
                        | R \leftarrow R \cup \{C\};
                     end
                else
                 i \leftarrow i+1;
                end
          end
     end
end
return R
```

- The risk of disclosing a sensor will be defined as the probability of having used the sensor for detecting the entity
- How is this probability computed?
 - Identify all combinations of sensors that would allow to detect the entity
 - Divide the number of combinations including the sensor by the total number of combinations

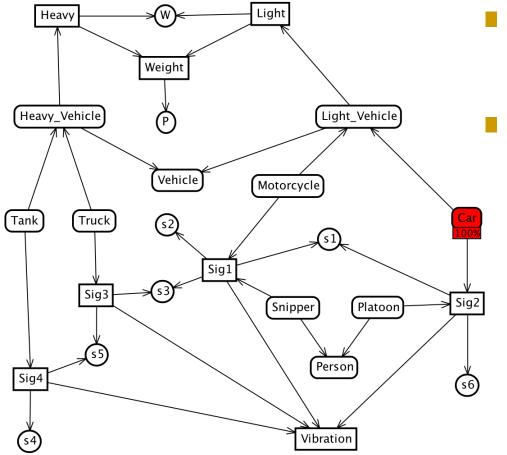


Risk Assessment





Risk Assessment Example



Entity to Disclose: Car

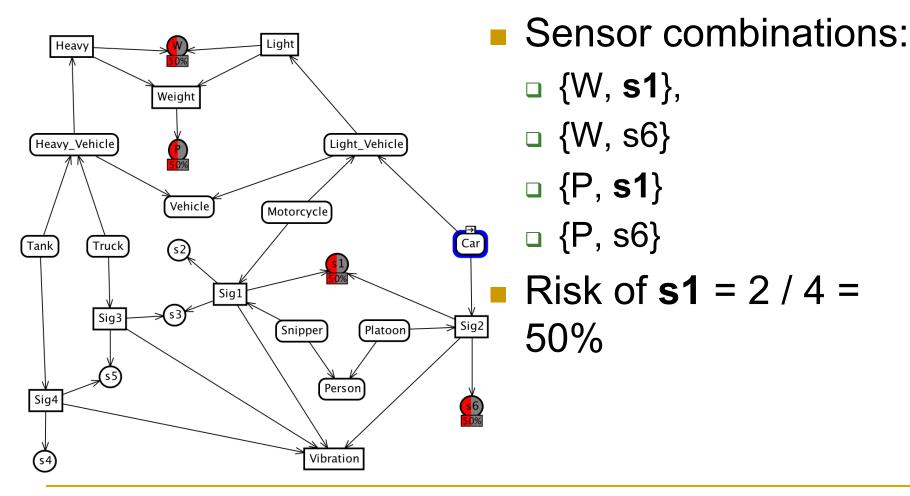
 Sensor combinations that allow the detection of a Car:

{vv, so}
{P, s1}

□ {P, s6}



Risk Assessment Example (continued)





First Evaluation

 Hypothesis: Using more abstract ontology classes reduces the risk

Evaluation:

- Obtained network from Army National Training Center
- □ For each child entity, C, assess the risk for each sensor $S \rightarrow Risk(S \mid C)$
- □ Then for the parent entity, P, assess the risk for each sensor S → Risk(S | P)
- $\square \operatorname{Risk}(S \mid C) \operatorname{Risk}(S \mid P)$
- Average differences



Second Evaluation Using Army National Training Scenario



- Scenario: subset of a military exercise dataset from the Army National Training Center
- 161 nodes
 - 51 sensors
 - 18 sensor types
 - □ 110 entities
 - Ontology has 63 classes of entities



Risk Assessment

| Sensor | Entity | | | | | | | | | |
|--------|---------|--------|--------|---------|---------|--------|---------|---------|--------|--|
| | P07 | P0 | Р | P82 | P8 | Р | 4UZ | 4U | 4 | |
| SEH | 14.29% | 12.50% | 8.00% | 33.33% | 33.33% | 8.00% | 18.18% | 18.18% | 16.98% | |
| SQ3IR | 14.29% | 12.50% | 24.00% | 33.33% | 33.33% | 24.00% | 36.36% | 36.36% | 22.64% | |
| SEC | 14.29% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 18.18% | 18.18% | 11.32% | |
| SNH | 0.00% | 0.00% | 36.00% | 0.00% | 0.00% | 36.00% | 100.00% | 100.00% | 52.83% | |
| SW | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 7.55% | |
| SQ5 | 14.29% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 9.09% | 9.09% | 22.64% | |
| SNU | 100.00% | 87.50% | 48.00% | 0.00% | 0.00% | 48.00% | 0.00% | 0.00% | 3.77% | |
| SN8 | 0.00% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 0.00% | 0.00% | 0.00% | |
| SW0 | 0.00% | 0.00% | 24.00% | 100.00% | 100.00% | 24.00% | 0.00% | 0.00% | 7.55% | |
| SEY2 | 14.29% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 27.27% | 27.27% | 11.32% | |
| SN9 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 1.89% | |
| SN90 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 1.89% | |
| SW3 | 0.00% | 12.50% | 12.00% | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 15.09% | |
| SQ3I6 | 57.14% | 50.00% | 56.00% | 33.33% | 33.33% | 56.00% | 36.36% | 36.36% | 22.64% | |
| SWP | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 16.98% | |
| SEYO | 57.14% | 50.00% | 16.00% | 0.00% | 0.00% | 16.00% | 36.36% | 36.36% | 37.74% | |
| SWN | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 9.43% | |
| SQ3Z | 14.29% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 18.18% | 18.18% | 20.75% | |



Risk Assessment (continued)

- Using more abstract classes in the ontology only helps to reduce the risk of the sensors involved in discovering the lower level entity type
- It also adds more sensors to the risk assessment, thus increasing the risk of all sensors in general
 - Thus risks of 0% will, in most cases, increase



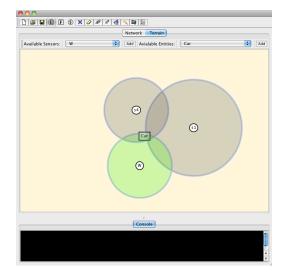
Risk Assessment

| Samaan | Entity | | | | | | | | | |
|--------|---------|--------|--------|---------|---------|--------|---------|---------|--------|--|
| Sensor | P07 | P0 | Р | P82 | P8 | Р | 4UZ | 4U | 4 | |
| SEH | 14.29% | 12.50% | 8.00% | 33.33% | 33.33% | 8.00% | 18.18% | 18.18% | 16.98% | |
| SQ3IR | 14.29% | 12.50% | 24.00% | 33.33% | 33.33% | 24.00% | 36.36% | 36.36% | 22.64% | |
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| SW | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 12.00% | 0.00% | 0.00% | 7.55% | |
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| SN8 | 0.00% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 0.00% | 0.00% | 0.00% | |
| SW0 | 0.00% | 0.00% | 24.00% | 100.00% | 100.00% | 24.00% | 0.00% | 0.00% | 7.55% | |
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| SQ3Z | 14.29% | 12.50% | 4.00% | 0.00% | 0.00% | 4.00% | 18.18% | 18.18% | 20.75% | |



Conclusions and Future Work

- ASP provides sensor disclosure risk estimates for different detections and sensors
- Users can choose explore different hypotheses for information release through the graphical interface
- We are currently adding spatial and temporal reasoning
- The choice of the appropriate level of abstraction for information release is not always intuitive, but it can be facilitated by the proposed approach







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Thank you!

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