Basics of Possibilistic PSYOPS for Decoy/Countermeasure Methods

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Abstract— Situational/threat assessment strategies have been studied for generations. Typically, these threat assessments utilize Bayesian belief networks and inference engines, based on decision tree technologies, to determine the likelihood of different deployment strategies and prevention methods (psyops). These are typically represented as a directed "acyclic" graph and utilize joint probability distributions, which are typically based on incomplete information as to the probabilities involved in various aspects of the current mission parameters. Bayesian believe network solutions are good at showing qualitative relationships between entities and have a compact and theoretically sound foundation. Problems arise when general questions or queries are required which cannot be specifically addressed by the Bayesian probabilities. Also, Bayesian methods tend to be computationally intensive. Here we look at fuzzy possibilistic methods that are more robust and less computationally intensive than standard Bayesian methods.

Keywords—countermeasures, PSYOPS, fuzzy possibilistics

1. Introduction

Part of the overall survivability analysis for battlefield planning and management includes looking at indicators that influence the emotions, motives, and objective reasoning of enemy forces. They purpose of this analysis is to understand how the behavior of organizations, groups and/or individuals might be influenced to accomplish mission objectives without the use of troops or military force. These possible psychological operations, called PSYOPS are employed when it is deemed they can induce or reinforce behavior favorable to U.S. objectives. They can become an important part of an overall battlefield strategy.

Here we present a fuzzy possibilistic network and inference engine, which provides robust situational assessments and general "what if" scenarios in the presence of inexact data measurements and information [3]. Our fuzzy possibilistic methods utilize conditional possibilistic technologies based on Renyi's generalized information theory, utilizing the concept of mutual information and joint informational memberships, rather than joint probabilities. These methods are excellent at illustrating qualitative relationships as well as possible relationship not attainable with Bayesian methods. These 1st and 2nd order possibilistic causal relationship structures allow confidence bounds to be consider within their conditional possibilistics and creates decisions with conditional possibility attributes [11]. They are more useful with general questions about a subject domain and are generally less computationally intense than Bayesian methods.

2. Conditional Possibilistics

Figure 1 illustrates the conditional possibilistics we developed, and they will be utilized within the decision processes for the example problem described below. In Figure 1, the arcs/lines represent causal relationships between states and the net represents joint possibilistics. There are two types of nodes [4]:

1. State: situational possiblistic models
2. Evidence: observations to be explained.

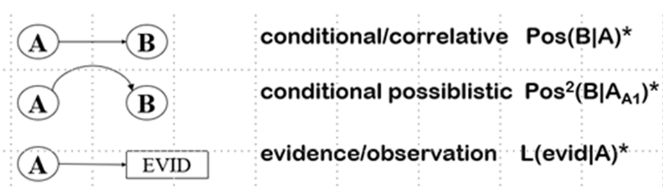

Figure 1. Conditional Possibilistics for PSYOPS Countermeasures

where:

- Pos(B/A) represents the possibility of B, given A was observed.

- Pos^2(B/A) represents the possibility of B given the possibility of A, with a confidence bound for A.
- L(evid/A) represents "what is the logical causality of the evidence/observation given A happened?

3. Fuzzy Information Fusion and Renyi's Entropy Measure

Figure 2 represents a processing flow for information analysis/processing. The process involves two main layers, the deductive process and the investigative process. The deductive process goes after assembling information that has been previously known while the inductive process (data mining) looks for patterns and associations that have not been seen before. The model illustrated in Figure 2 is the deductive process used to detect previously known patterns in many sources of data by searching for specific information signatures and templates in data streams to understand the state of the intelligence knowledge [13]. As the systems continues to evolve in complexity, the number of objects, situations, threats, sensors and data streams dramatically increase, presenting a very complex challenge for advanced fusion system designers. In order to keep the system "on-top" of its data environment is to have data mining operations going on in the background at all times, finding new associations and evolving the templates and information correlations [6].

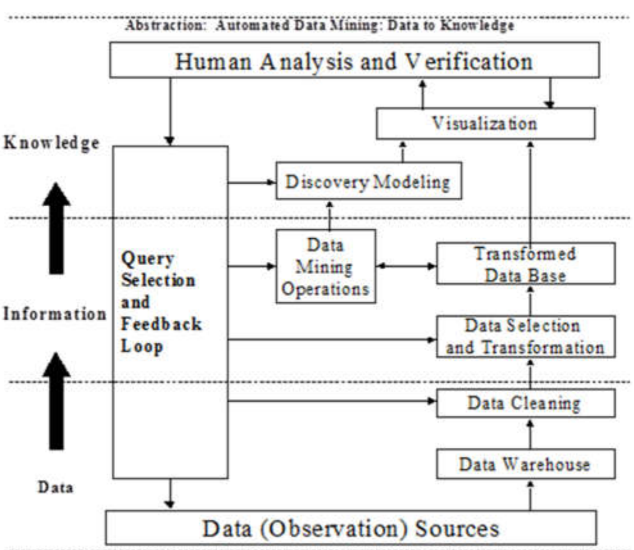

Figure 2. Data/Information Flow for Data Mining

In both data mining and data fusion, feature selection or feature transforms are important aspects of any system. Optimal feature selection coupled with pattern recognition leads to a combinatorial problem since all combinations of available features must be evaluated before deciding how to fuse the information available. Another such criterion is the joint ***Mutual Information*** between the features and the class labels [13]. It can be shown that Mutual Information minimizes the lower bound of the classification error. However, according to Shannon's definition this is computationally expensive. Evaluation of the joint Mutual Information of a number of variables is plausible through histograms, but only for a few variables. If we look toward a different definition of Mutual Information we find a different result. Using Renyi's entropy instead of Shannon's, combined with Parzen density estimation, leads to expression of Mutual Information with significant computational savings. As a part of this study, we extended Renyi's method for Mutual Information to multiple continuous variables and discrete class labels to learn linear dimension-reducing linear feature transforms for data fusion and parameter estimation utilizing competing parameter measures [5].

We applied Renyi's entropy-based Mutual Information measure to create fuzzy membership functions that can be used to rapidly asses the Mutual Information content between multiple measurements of a given parameter from different sensors [1]. We introduce the Mutual Information measure based on Renyi's entropy, and describe its application to Fuzzy Membership Functions that were used transform multiple parameter measures and error estimates into a single parameter and error bound estimate for the parameter.

3.1 Mutual Information

We apply Renyi's entropy definitions instead of the standard Shannon definition because of its computational advantages. For a continuous variable ***Y***, Renyi's quadratic entropy is defined as:

$$H_R(Y) = -\log \int_y p(y)^2 dy$$

It turns out that Renyi's measure, combined with the Parzen density estimation method using Gaussian kernels, provides significant computational savings, because a convolution of two Gaussians is still a Gaussian. If the density $p(y)$ is estimated as a sum of symmetric Gaussians, each centered at a sample y_i as:

$$p(y) = \frac{1}{N}\sum_{i=1}^{N} G(y - y_i, \sigma I)$$

then it follows that the integral above equals:

$$\int_y p(y)^2 dy =$$

$$= \frac{1}{N^2}\int_y \left(\sum_{k=1}^{N}\sum_{j=1}^{N} G(y - y_k, \sigma I) G(y - y_j, \sigma)\right) dy$$

$$= \frac{1}{N^2}\sum_{k=1}^{N}\sum_{j=1}^{N} G(y_k - y_j, 2\sigma I)$$

Thus, Renyi's quadratic entropy can be computed as a sum of local interactions as defined by the kernel, over all pairs of samples.

3.2 Maximizing Mutual Information

To make use of this convenient property, we make use of fuzzy membership functions and the natural way they demonstrate local interactions to find a function which maximized Mutual Information among sensor measurements [7]. For each factor in the PSYOPS/battlefield scenario, a fuzzy membership normalization factor is formed and then each measurement is mapped onto each membership normalization function:

$$Y_i = E_{j=1}^{n}\left(e^{\frac{-(M_i - M_j)^2}{2*\sigma_i^2}}\right)$$

Once all the curves have been populated, we compute the mean fuzzy membership value for each function:

$$Y_i = E_{j=1}^{n}\left(e^{\frac{-(M_i - M_j)^2}{2*\sigma_i^2}}\right)$$

$$Y_{max} = \max_{i=1,n}(Y_i)$$

The normalization function with the highest mean membership represents the normalization mapping with the highest Mutual Information and is therefore given the highest weighting in determining the measurement value to report. The weighting factors are then determined for rolling up the measurements and error bounds into a single parametric estimation [8]:

$$W_i = Y_i \Big/ \sum_{j=1}^{n} Y_j$$

where the ***Wis*** are the weighting factors. Figure 3 illustrates the process.

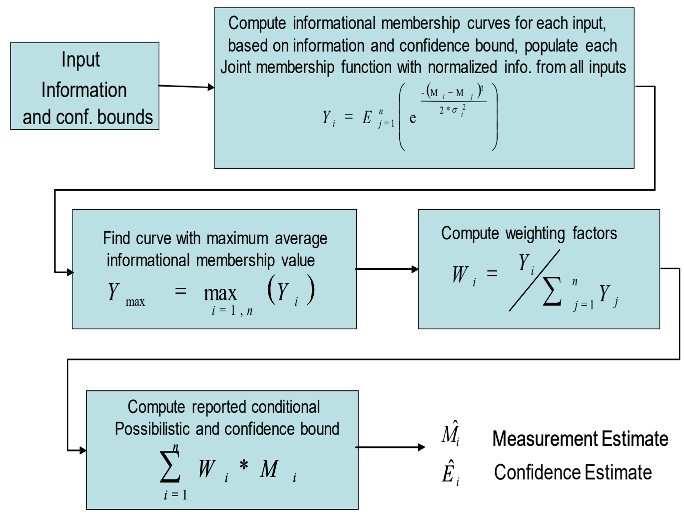

Figure 3. Weighted Fuzzy Parametric Estimation Process

4. SAMPLE SCENARIO

Figure 4 (at the end of the paper) illustrates the sample possibilistic situational/threat assessment scenario that was created for this paper. It includes a variety of information sources from submarines to UAVs and many others. Much evidence/observations are available to make decisions about how to proceed, given the mission objectives. Some of these questions might include:

- What decisions are possible, based on the evidence/observations:
- What are the confidence bounds on the decisions, given the evidence/observations?
- What changes in conditions/observations and/or confidence bounds on the conditions/

observations might lead to different decisions?

Based on the answers to these questions, a situational assessment would be made to answer threat questions like:

- What threats are in what locations, with what confidence bounds?
- What units are in what locations?
- What type of attacks/missions are possible?
- When can it be predicted that significant events will occur, with what confidence bounds?
- What are the possible avenues of approach?

Figure 5 (at the end of the paper) illustrates a possible possibilistic situational assessment, based on the conditional possibilistics illustrated in Figure 1. Many factors, including things like weather and terrain constraints, are accounted for in the initial assessment. Possible troop movements are indicated.

4.1 Possibilistic Assessment Results

Based on the conditional possibilistic assessment shown in Figure 5, the results would be:

- Decision 1: where to send troops?
    - Send troops to area 1
    - Send troops to area 2
- Decision 2: which route should troops take?
    - Send troops by northern route
    - Send troops by central route
    - Send troops by southern route

All combinations are possible, given all the evidence/observations that were available from the various information sources. The highest possibility for success indicates to send troops to area 2 via the northern route. This combination constitutes the highest mutual information calculation. The highest possibility of success is from the norther route. However, there is also a high possibility of creating an effective deception plan using this route also. Much of this is based on the confidence of weather reports and the confidence on our assessment of the enemy's intelligence on our troops and possible troop movements. Also, subtle changes in confidence levels or evidence could change the route or the area, or both. Investigating PSYOPS possibilities provides highest possibility of survivability. Questions to be answered are:

- Are there PSYOPS activities that can prevent the necessity for a "hard kill?"
- If so, what type of PSYOPS?
    - Political
    - Propaganda
    - Cultural
    - Other

4.2 Possibilistic Assessment Results with PSYOPS

Figure 6 (at the end of the paper) illustrates the information shown in Figure 5, plus the addition of a PSYOPS evaluation. The conditional possibilistic assessment results with PSYOPS provides the following decisions:

- Decision 1: where to send troops?
    - Send troops to area 1
    - Send troops to area 2
- Decision 2: which route should troops take?
    - Send troops by northern route
    - Send troops by central route
    - Send troops by southern route
- Decision 3: use PSYOPS plan rather than sending in troops.

Again, all combinations are possible given all the evidence/observations available. The highest conditional possibility for success and survivability indicates to use PSYOPS rather than a hard kill scenario [12]. The highest conditional possibilistic survivability assessment indicates to use a cultural PSYOPS approach. Much of this is based on the confidence of our intelligence on their culture and their state of political pressure/influence, propaganda influence, etc. Again, subtle changes in confidence levels or evidence could change the decision from PSYOPS to hard kill. The advantage of the fuzzy possibilistic measures is there simplicity of computation, allowing real-time, ad-hoc changes and "what if" scenarios to be explored in the field and rapid decisions implemented based on current information/observations.

5. Conclusions and Discussion

Data/information fusion is critical to real-time, effective situational/threat assessments [10]. The use of possibilistic logic provides a more efficient and, we believe, better assessment of overall scenario/hypothesis testing. The conditional fuzzy possibilistic approach can be a valuable tool in survivability assessment. One assumption threaded into the computations is that the system allows fluid communications between the heterogeneous information sources [2]. If this is not possible, data fusion can be brittle and can fail. The flow from a system-level to decision level design is essential for effective fusion systems for tomorrow's intelligence processing and decision support systems [9].

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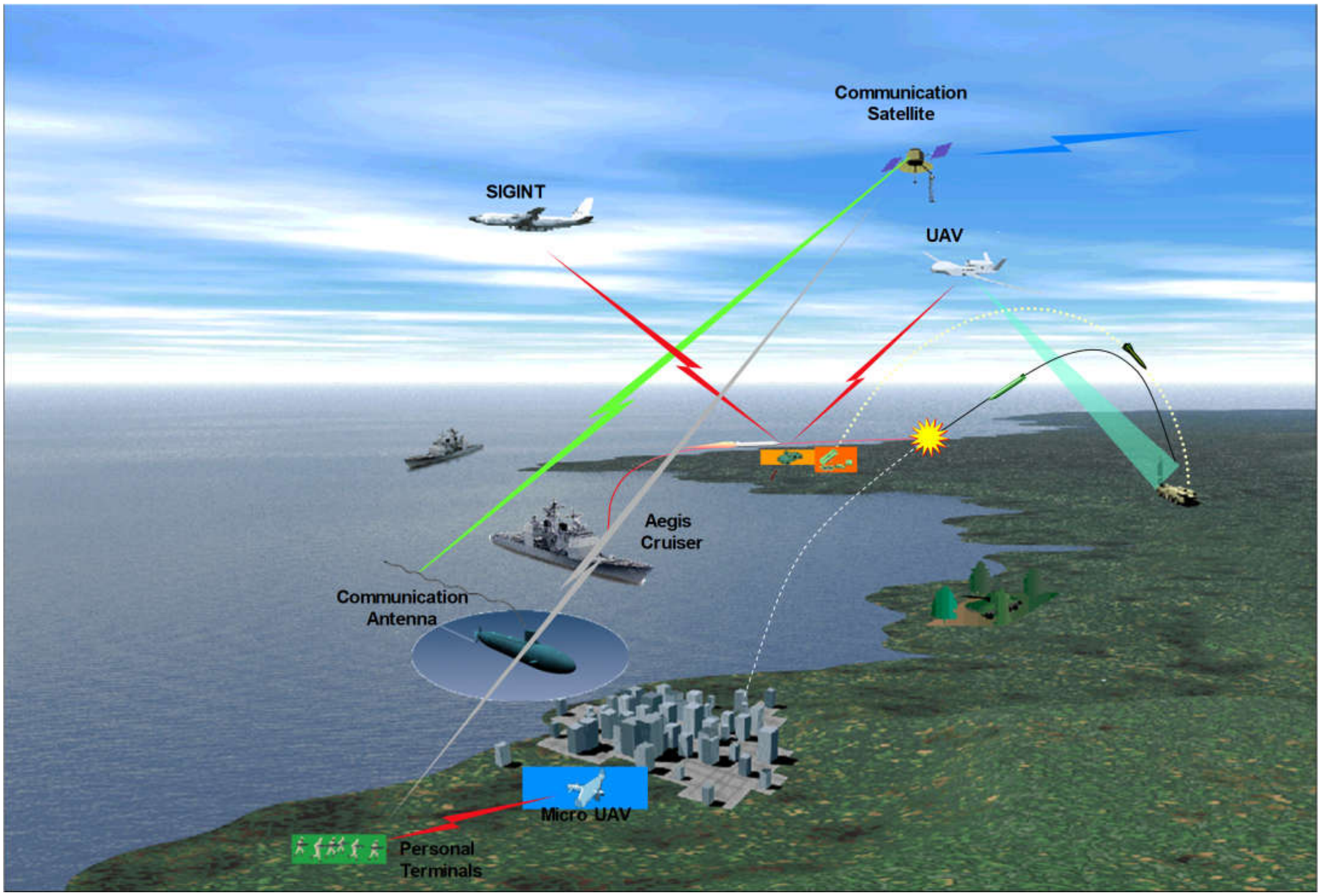

Figure 4. Sample Mission/Battlefield Situation Scenario

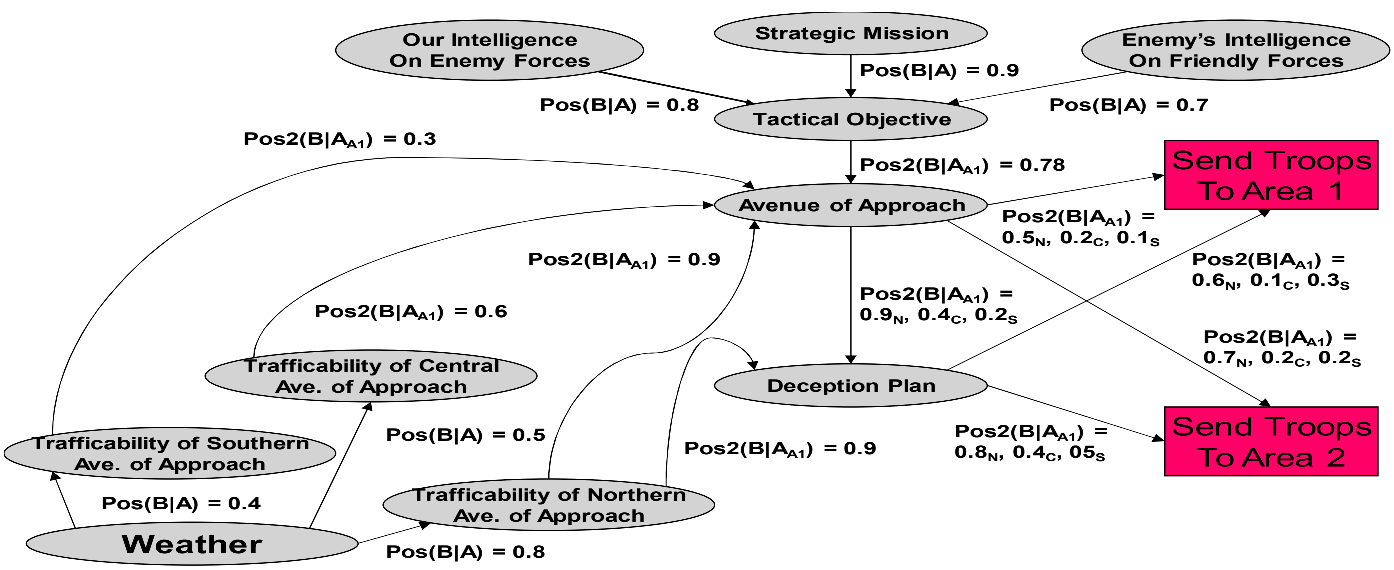

Figure 5. Conditional Possibilistic Assessment Example based on Figure 4 Scenario

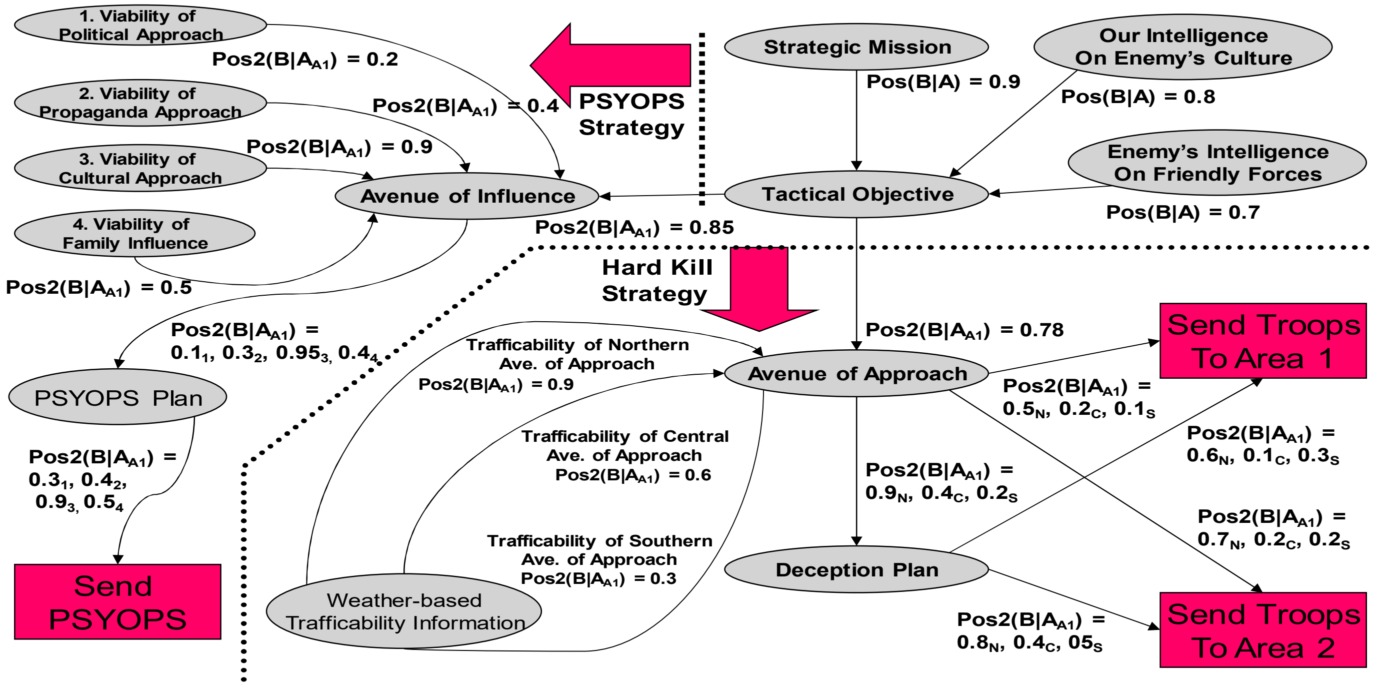

Figure 6. Conditional Possibilistic Assessment Including PSYOPS Strategies