Aggregating Complementary and Contradictory Information for Military Decision Making

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Abstract

Timely, relevant, and accurate information is critical to the military decision making process. The Value of Information (VoI) determination prioritizes information importance based on the applicability of information to a specific operation. A significant challenge of producing an accurate VoI metric for military decision making arises when there are multiple pieces of complementary or contradictory (C/C) information relating to the same situation or event. The goal of this research is to utilize Bayesian aggregation techniques to evolve a fuzzy-based VoI system such that it can effectively model how military intelligence analysts reason over multiple pieces of C/C information. The basic approach proposed here is to first emulate the current fuzzy-based VoI system with one or more Bayesian reasoning methods, then augment the new models with the capability to aggregate multiple pieces of C/C information.

Keywords: information aggregation, value of information, military decision making, Bayesian decision making

1. INTRODUCTION

In every field there are limited processing resources in terms of technological tools and human analytical expertise. This limitation, along with the huge amounts of data that are gathered every day, makes it impossible for businesses, government, and other organizations to effectively analyze pertinent available data for real time decision making.

Similarly, this classic information overload problem exists with respect to intelligence analysis and other operations in the military environment. As part of collective intelligence undertakings there are vast amounts of data made available every day; monitoring and analyzing these data are great challenges for military intelligence agencies. Gaining actionable information and intelligence within a time-constrained setting is vital in military environments. Moreover, information assessment to judge and analyze the high value information, termed as Value of Information (VoI), is very critical for military operations.

The intelligence process must work hand in hand with the military operations process in a continuous manner to provide intelligence vital to the operations process. "Intelligence about the enemy, the battlefield environment, and the situation allows the commander and staff to develop a plan, seize and retain the initiative, build and maintain momentum, and exploit success." (US Army, 2006) Prioritizing and calculating the value of a piece of information are challenging tasks. It "depends upon human judgment and a multiple step process requiring intelligence collectors and analysts to make decisions within a host of differing operational situations." (Hammell II, Hanratty, & Heilman, 2012)

Recent work on the Value of Information (VoI) problem has developed a system using a Fuzzy Associative Memory (FAM) architecture and offers an effective framework for determining the VoI based on the information's content, source reliability, and latency as well as consideration of the mission context (Hanratty, Newcomb, Hammell, Richardson, & Mittrick, 2016). Subsequent work has been undertaken to address the issue of how to update or revise the VoI determination when additional information is received that may be complementary or contradictory with respect to an earlier piece of information. Initial ideas to simplistically utilize the characteristics of the VoI determination were shown to be untenable (Hammell, Hanratty, & Miao, 2016); further investigations produced a complex multiple-FAM system based on additional subject matter expert knowledge elicitation efforts (Hanratty, Heilman, Richardson, & Caylor, 2017).

Work conducted under the administration of the Intelligence Advanced Research Projects Activity (IARPA) offers perhaps a different approach (Intelligence Advanced Research Projects Activity, n.d.). A past research program entitled Aggregative Contingent Estimation (ACE) (Aggregative Contingent Estimation, n.d.) focused on developing methods for obtaining, evaluating, and aggregating the opinions of multiple experts. Research within the ACE program defines methods of Bayesian probability or degree-of-belief interpretation of probability for expert opinion aggregation. Probabilistic forecasts on events can be generated by mathematical aggregation of judgments similar in accuracy to individual expert judgment and group deliberation by experts on an event. While some of this work appears to be aimed at knowledge elicitation activities, it appears that approaches used in this area could be modified to combine multiple pieces of information with varying levels of agreement (complementary) and disagreement (contradictory).

The goal of this research is to leverage the IARPA Bayesian aggregation ideas to evolve the fuzzy-based VoI system such that it can effectively model how military intelligence analysts reason over multiple pieces of complementary/contradictory (C/C) information. The basic approach proposed here is to first emulate the current fuzzy-based system with one or more Bayesian reasoning methods, then augment the new models with the capability to aggregate multiple pieces of C/C information.

The remainder of this paper is organized as follows: First, background material pertaining to VoI and the initial fuzzy-based system developed to calculate VoI for a single piece of information is provided. Following that, a more detailed discussion of the complementary/contradictory problem and past research related to the issue is presented. Then, a general discussion of Bayesian reasoning and the proposed approach for using two different Bayesian models in this investigation is outlined. Finally, some conclusions are offered.

2. BACKGROUND

Tactical strategy and military actions are dependent on timely, relevant, accurate information. Qualified covert human intelligence sources, surveillance technologies, and devices for interception of communications are some examples of intelligence gathering sources for complex military environments. The decision making cycle is a cognitive process that selects the best choice from among a set of possible choices; good decisions are highly dependent on access to the appropriate information. In a dynamic, time-constrained decision making environment it is crucial to have some method for prioritizing or ranking the value of individual pieces of information related to a specific military context.

This section provides background information on making value of information determinations, fuzzy logic, and the fuzzy-based system that has been developed to help automate the information valuation process.

Value of Information (VoI)

The U.S. Army Military Decision Making Process (MDMP) is a seven step analytical procedure with over 100 sub-steps (US Army, 2005). Large amounts of heterogeneous data from many resources must be transformed into meaningful information to feed the MDMP. In a dynamic, complex environment it is critical to have some way for military intelligence analysts to prioritize all this information based on its value; this is the basis of the Value of Information (VoI) problem. Further, automation of such a method is required to meet the needs of the analysts in the typical time-constrained decision environment.

Determining the value of information based on some VoI metric can narrow down the large amount of disparate information into some sort of prioritized list. U.S. military doctrinal guidance calls for each piece of information to be judged using the two criteria of "Source Reliability" and "Information Content" (US Army, 2006). Tables 1 and Table 2 illustrate the categories used within those criteria. (See the Appendix for larger versions of the tables.)

A	**Reliable**	**No doubt** of authenticity, trustworthiness, or competency; has a history of complete reliability
B	**Usually Reliable**	**Minor doubt** about authenticity, trustworthiness, or competency; has a history of valid information most of the time
C	**Fairly Reliable**	**Doubt** of authenticity, trustworthiness, or competency but has provided valid information in the past
D	**Not Usually Reliable**	**Significant doubt** about authenticity, trustworthiness, or competency but has provided valid information in the past
E	**Unreliable**	**Lacking** in authenticity, trustworthiness, and competency; history of invalid information
F	**Cannot Be Judged**	**No basis** exists for evaluating the reliability of the source

Table 1- Source Reliability Evaluation (US Army, 2006)

1	**Confirmed**	**Confirmed** by other independent sources; **logical** in itself; **Consistent** with other information on the subject
2	**Probably True**	Not confirmed; **logical** in itself; **consistent** with other information on the subject
3	**Possibly True**	Not confirmed; **reasonably logical** in itself; **agrees with some** other information on the subject
4	**Doubtfully True**	Not confirmed; possible but **not logical**; **no other information** on the subject
5	**Improbable**	Not confirmed; **not logical** in itself; **contradicted** by other information on the subject
6	**Cannot Be Judged**	**No basis** exists for evaluating the validity of the information

Table 2 - Information Content Evaluation (US Army, 2006)

While providing the above direction, U.S. military doctrinal guidance does not offer a method to combine the ratings of the two criteria into any sort of information value determination. It is also easy to understand that the two criteria of Source Reliability and Information Content are not enough to fully judge the value of a piece of information. Hammell, et al. (2012) offer two additional criteria: timeliness and mission context. Timeliness portrays the time frame since a piece of information was obtained while mission context describes the operational tempo and decision cycle time available for planning, preparation, and executing a specific mission.

Recent work under the auspices of the U.S. Army Research Laboratory has led to the development of a fuzzy-based VoI prototype system (Hammell et al., 2012). With guidance from military intelligence analyst Subject Matter Experts (SMEs), fuzzy rules were created to populate a Fuzzy Associative Memory (FAM) architecture (Hanratty, Heilman, Dumer, & Hammell, 2012). This system is briefly described below after a short introduction to fuzzy logic.

Fuzzy Logic Systems

Fuzzy set theory was introduced by Professor Lotfi A. Zadeh in 1965 (Zadeh, 1965) as an alternative to classical set theory. In classical set theory a value either belongs to a set (with degree of membership = 1) or it does not belong to the set (degree of membership = 0). By contrast, in fuzzy set theory a value can belong to a set with membership degree in the range 0 to 1; that is, it can fully belong, not belong, or belong with a partial membership degree.

Fuzzy Logic is the answer to the real-life situations in computing and decision-making where factors are not crisp and deterministic. Fuzzy logic can solve complex problems with simple and basic rules. Since its inception, fuzzy logic has been used in a myriad of applications, such as to add intelligence to robotics, video games, train systems and transportation; camera stabilization systems, automobile braking systems, and home appliances such as washing machines; and business fields of practice such as project management and health insurance underwriting (Lughofer, 2011; Kumar & Jain, 2012).

Figure 1 illustrates the decomposition of the "Height" domain into three Fuzzy sets: "Short", "Average", and "Tall". The different units of height measurements are marked on the x-axis

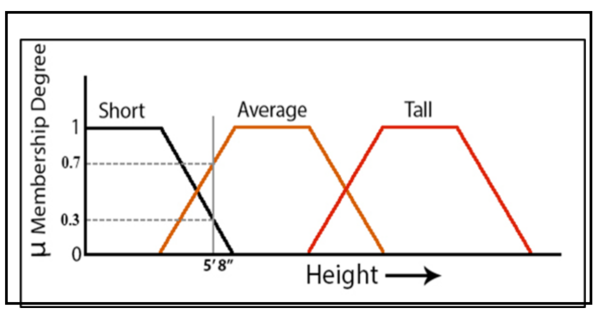


Figure 1 – Fuzzy Domain Decomposition

and the degree of membership (from 0 to 1) is marked on the y-axis. A height input value could be part of the "Short" set; but, at the same time can belong to "Average" with some degree of membership. For example, a person with a height of 5'8" has a membership degree (μ) of 0.3 in "Short", 0.7 in "Average" and 0.0 in "Tall".

In Figure 1, the membership functions (fuzzy sets) define the degree of membership for a value; the shape of these three fuzzy sets determines the membership functions. The shape of fuzzy sets can be triangular, trapezoid, or other types of curves.

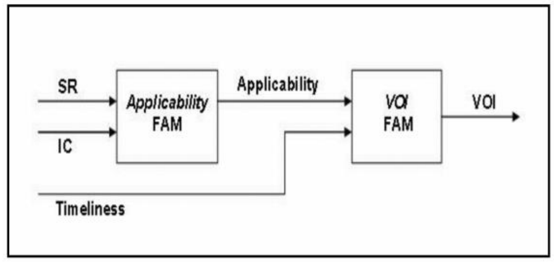
One use of fuzzy logic is to develop fuzzy inference systems; these systems provide the ability to perform approximate, or fuzzy, reasoning. Linguistic variables are an important concept in fuzzy inference (Zadeh, 1975). A linguistic variable is used to approximately characterize relationships and values. As in the above example, numbers can be used to characterize a person's height, but using words instead might provide the categories of short, average, and tall. Additionally, fuzzy systems are known to be good at approximate reasoning where information is uncertain, incomplete, imprecise, and/or vague (Magnanai & Montesi, 2010; Zadeh, 1987).

Fuzzy-based VoI System

As noted earlier, recent research has led to the development of a fuzzy-based VoI prototype system (Hammell, et al., 2012). A Fuzzy Associative Memory (FAM) model was chosen to construct the prototype VoI system. A FAM is a multi-dimensional table where each dimension corresponds to one of the input domains. Fuzzy if-then rules are represented in the FAM; the inputs (rule antecedents) are used as indices to access the appropriate "cell" of the FAM, and the value in the cell represents the output (rule consequent). A fuzzy rule with two antecedents has the form "If *X* is *A* and *Y* is *B* then *Z* is *C*" where *A* and *B* are fuzzy sets over the two input domains and *C* is a fuzzy set over the output domain.

The overall architecture of the prototype fuzzy system is shown in Figure 2. The VoI system uses three inputs: source reliability, information content, and timeliness; the concept of various mission contexts is accounted for by having multiple models. The output of the model is the VoI metric. Instead of using one 3-dimensional FAM, two 2-dimensional FAMs were used for the reasons presented in (Hammell, et al., 2012).

Figure 2 - Prototype Fuzzy VoI System



Architecture (Hammell, Hanratty, & Heilman, 2012)

The fuzzy rules represented in the FAMs capture the relationships between the input and output domains. For example, an actual rule in the Applicability FAM might be: "if *Source Reliability* is 'Usually Reliable' and *Information Content* is 'Probably True', then *Information Applicability* is 'Highly Applicable'." Knowledge elicitation from military intelligence SMEs was used to construct the fuzzy rules (Hanratty, et al., 2012).

More detailed descriptions of the FAMs, the fuzzy rule bases, the domain decompositions, and other implementation aspects of the system can be found in (Hanratty, et al., 2013). The series of surveys and interviews with SMEs that were used to integrate cognitive requirements, collect functional requirements, and elicit the fuzzy rules are presented in (Hanratty, et al., 2012). The VoI prototype system, the initial version and phase 2, has been demonstrated to the SMEs. Both versions of the prototype and its output have met military intelligence subject matter expert expectations (Hanratty, et al., 2016).

3. COMPLEMENTARY / CONTRADICTORY INFORMATION

The fuzzy-based VoI system just described was developed to handle individual pieces of information. The complex decision making processes used in the military certainly require the ability to assimilate information from disparate sources, as well as combine new information with previously known information. The idea that new information may or may not match the previous information complicates the situation; this is the complementary/ contradictory (C/C) information problem

Simplistically, it is easy to understand that the VoI ratings will obviously change as time passes since *timeliness* is one of the input characteristics. However, it is also apparent that the acquisition of new information will impact past VoI valuations. Examples of this include

(1) a change in the *source reliability* of a particular source, or (2) obtaining a new piece of information that contradicts or conflicts previous information. This latter problem is of particular interest to military intelligence analysts.
To that end, the next step in the evolution of the fuzzy-based VoI system has included research to evaluate how military intelligence analysts reason across multiple pieces of information, especially considering when multiple pieces are complementary or contradictory in nature with respect to the same event. This section describes previous related research from the literature and also VoI-specific investigations.

Data Conflict Strategies
In the literature, the idea of having complementary or contradictory information is termed as 'data conflict' (Bleiholder & Naumann, 2008). Handling data conflict has been an active research area in data fusion for many years. Bleiholder & Naumann (2008) survey data conflict strategies and provide a classification identifying the three basic classes as shown in Figure 3.

Space limitations do not allow for a detailed discussion of the three classes of strategies or the many systems that have been proposed and developed for handling conflicting data. Such a discussion is presented in (Miao, et al., 2015) along with more information about why none of these approaches or systems are well suited towards the military environment.

Briefly, the military problem domain rules out using strategies within the 'conflict ignorance' or 'conflict avoidance' classifications. The 'conflict resolution' techniques are also problematic in that data training in this domain is often not possible. Additionally, some of the techniques in this class produce values that may not be useful (such as the most recent, preferred, average, or random). While the approaches that consider accuracy, freshness, and dependence related to sources are interesting, there is no general approach on how to combine these properties.

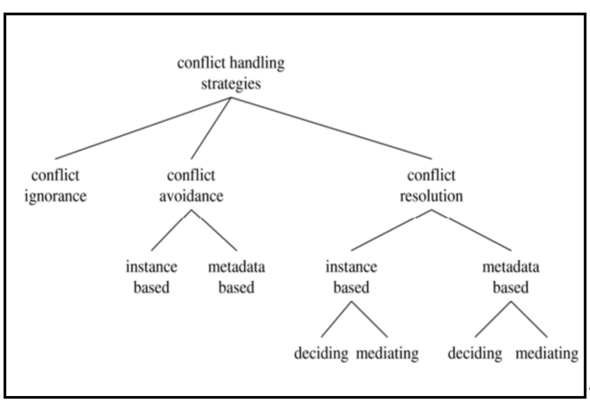


Figure 3 – Data Conflict Strategies (Bleiholder & Naumann, 2008)

VoI-related C/C Work
Given that data conflict strategies reflected in the literature did not provide a method for integrating C/C information in the VoI system, other approaches were considered. Recently, two avenues of research were undertaken to specifically address the issue within the VoI context.

The first research methodology sought to retain the original FAM architecture in the VoI system. Recall that within the prototype VoI system the *information content* characteristic is concerned with whether a piece of information agrees/disagrees, is logical/illogical, or is consistent/inconsistent as compared to other information. The work presented in (Miao, et al., 2015) talked about approaches for modifying the *information content* grade of a previously obtained piece of information to reflect a change in VoI based on the acquisition of new complementary or contradictory information. One approach was to conduct a knowledge elicitation session with the SMEs to get information about how they perceive the change in VoI when new complementary/contradictory information is obtained, and then "backwards solve" in the system shown in Figure 2 to find the new IC value that would be required to produce the new VoI determination. This approach was investigated and reported on in (Hammell, et al., 2016).

The results showed that this simplistic method was not feasible. The "reverse solving" idea resulted in a new FAM with empty cells; that is, there were fuzzy rules missing for some sets of input values. Three approaches to fill in the missing rules via rule base completion techniques were tried but none produced reasonable results. The final attempt to salvage this overall methodology looked to see if perhaps the SMEs did not use the missing rules when reasoning across C/C information; the experiment in which SMEs aggregated C/C information demonstrated this was not the case. Thus, it was determined that a more complete SME experiment, along with a different approach, was required.

The second method included the more complete SME experiment along with a comprehensive change in the fuzzy-based VoI system (Hanratty, et al., 2017). The experiment consisted of using 20 SMEs from Fort Huachuca, Arizona in a study that required SMEs to provide their perceived change in information applicability given new information that was complementary or contradictory in nature. One hundred different combinations of information were used in the experiment.

The results led to a significant modification to the original VoI FAM architecture. Two additional FAMs were added; one called the "Cognitive Group FAM" and another termed the "Applicability Conditional Adjustment FAM". While the ensuing architecture is appreciably more complex, early results are promising. The system has yet to undergo a comprehensive, statistically significant experiment to judge its efficacy. The complete description and results can be found in (Hanratty, et al., 2017).

Table 3 summarizes the results achieved by the different approaches outlined in this section.

	Approach	Results
First Method	Backwards Solve for New Information Content (IC)	FAM had empty cells. Missing fuzzy rules for some sets of input values.
	Rule base completion to fill FAM entries	Provided unreasonable rules.
	Check to see if SMEs did not use missing rules	SMEs do in fact need rules corresponding to the inputs for which the rules are missing.
Second Method	More complete SME experiment	Significantly modified FAM architecture that is appreciably much more complex. The new system not yet validated comprehensively.

Table 3 – Summary: Data Conflict Approaches and Results

4. A BAYESIAN APPROACH

Work conducted under the administration of the Intelligence Advanced Research Projects Activity (IARPA) offers perhaps a different approach to the C/C problem (Intelligence Advanced Research Projects Activity, n.d.). A past research program within IARPA entitled Aggregative Contingent Estimation (ACE) (Aggregative Contingent Estimation, n.d.) focused on developing methods for obtaining, evaluating, and aggregating the opinions of multiple experts. ACE program research defined methods of Bayesian probability or degree-of-belief interpretation of probability for expert opinion aggregation. While some of this work seems like it might be especially useful for knowledge elicitation activities, further investigation suggested that selected approaches could be modified to combine multiple pieces of information with varying levels of agreement (complementary) and disagreement (contradictory).

A primary goal of the ACE program was to dramatically improve the accuracy, precision, and timeliness of intelligence forecasts, which can be listed in a wide range of event types. (Aggregative Contingent Estimation, n.d) Many of the articles produced under the ACE program are about predication and forecast based on the wisdom of the crowd approach. In one paper that is particularly applicable to our problem domain, a cognitive modeling approach was developed which joined the classic psychology theories of knowledge representation and judgment for combining people's rankings of items. (Lee, Steyvers, & Miller, 2014) In that research, the human behavior and individual differences were observed to determine how each individual's judgment with a different level of knowledge can lead to observed ranking of data in behavioral tasks. This cognitive model implementation uses a Bayesian graphical Thurstonian model, and uses computational sampling to infer an aggregate ranking as well as measures relating to individual expertise. The results are compared with the Borda count method and demonstrate a slight advantage in using their proposed Thurstonian model.

The Borda count model is a traditional statistical method for aggregating rankings and represents the Wisdom of the Crowd effect. The format of this statistical method assigns points to each element for the placed position in a ranking system; it then sorts out the combined points to generate an aggregate ranking result. Borda count produces combined rankings that typically perform well relative to individuals (Lee et al., 2014).

The Bayesian Thurstonian ranking model is one of the oldest and most well-known order statistic models. (Johnson & Kuhn, 2013) It is based on classic representational ideas in psychology dating back to Louis Leon Thurstone in the 1920s who was a U.S. pioneer in the fields of psychometrics and psychophysics. (Thurstone, 1927) The Thurstonian model has two basic assumptions; one is "that the attributes of stimuli can be modeled in terms of a psychological continuum, represented by coordinates on a latent dimension" (Lee et al., 2014). The other assumption is that these representations have some variability associated with them. The Thurstonian model to be used in the research described herein will be patterned after the extended model reported in (Lee et al., 2014). Their model allows variation in the widths of the distributions, which is a generalization that supports the assumption that individual differences in knowledge exist.

The proposed approach for this research involves implementing both the Bayesian Thurstonian and Borda count methods with respect to the VoI problem domain. Initially, both methods will be used to attempt to replicate the VoI determinations produced by the original fuzzy-based VoI system. Results from the comparisons will illustrate how well these probabilistic approaches compare to the fuzzy-based approach. The same data and experimentation methods used to validate the original system with the SMEs will be used to assess the Thurstonian and Borda count systems.

Once one or both of these new models produces comparable results to the original fuzzy-based FAM approach, the model(s) will be extended to tackle situations dealing with multiple pieces of complementary and contradictory information. The results here will be compared to those produced by the modified FAM architecture reported in (Hanratty, et al., 2017). Again, the experiments and data used to evaluate the new models will be the same as those used in the modified fuzzy-based system.

Preliminary investigation indicates that both the Thurstonian and Borda count systems can be implemented with the Just Another Gibbs Sampler (JAGS) software package (Plummer, 2003). JAGS is a simulation program for analysis of Bayesian hierarchical and graphical models and was used in the work reported in (Lee et al., 2014).

Bayesian reasoning appears to be an appropriate approach to consider for the VoI problem domain. The basic idea of Bayes' theorem is that, in the beginning, a probability *X* can be given about an event based on current knowledge. Later, as additional information is gained, the probability can be updated (Broemeling, 1985). That is, the initial assessment was not wrong - it was just based on incomplete information. This is basically the crux of updating a VoI determination based on receiving new information; the fact of whether the new information is complementary or contradictory in nature will need to be considered in the updated probability calculations.

One concern with how the Bayesian approach can be applied revolves around the need to have the SMEs define conditional and/or joint probabilities. However, the work in (Por & Budescu, 2016) presents a method for eliciting subjective joint probabilities from SMEs without having to explicitly ask for them. The authors use a pair-wise comparison technique which shows promise to augment or replace conventional elicitation approaches. The potential usefulness of this approach will need to be investigated further.

5. CONCLUSIONS

In a military environment, prioritizing the value of information is a time consuming and challenging task done by military intelligence analysts. Recent work has been done to produce a fuzzy-based system to assist in automating the Value of Information (VoI) determinations.

An even more difficult situation exists when trying to model how military intelligence analysts reason over multiple pieces of information, especially considering that information related to the same event can be complementary or contradictory in nature. Examination of the original fuzzy-based system in this context demonstrated that it could not handle such a problem with simple modification. A more complex fuzzy-based FAM architecture has been developed; results are promising but not yet validated.

The goal of this research is to leverage the Bayesian aggregation approaches developed under the IARPA ACE program to evolve the fuzzy-based VoI system such that it can effectively model how military intelligence analysts reason over multiple pieces of complementary/contradictory (C/C) information. The basic approach proposed here is to first emulate the current fuzzy-based system with the Bayesian Thurstonian method and the Borda count method. Once that is complete, the new models will be extended with the capability to aggregate multiple pieces of C/C information. The outcome of this work will be a comparison with the fuzzy-based models to judge the relative efficacy of each, and capitalize on whichever model offers the most advantages.

There are unprecedented types and amounts of data available to military intelligence analysts. The ability to make crucial decisions on today's battlefield is highly dependent on accurate and timely information, along with the ability to process this information quickly enough to gain the advantage by getting inside an adversary's decision cycle. The ongoing research reported herein related to automating value of information determinations is of great

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importance to the military decision making process.

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Appendix
Larger Version of Tables

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6	**Cannot Be Judged**	**No basis** exists for evaluating the validity of the information

Table 2 - Information Content Evaluation (US Army, 2006)

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	Approach	Results
First Method	Backwards Solve for New Information Content (IC)	FAM had empty cells. Missing fuzzy rules for some sets of input values.
	Rule base completion to fill FAM entries	Provided unreasonable rules.
	Check to see if SMEs did not use missing rules	SMEs do in fact need rules corresponding to the inputs for which the rules are missing.
Second Method	More complete SME experiment	Significantly modified FAM architecture that is appreciably much more complex. The new system not yet validated comprehensively.

Table 3 – Summary: Data Conflict Approaches and Results