Empirical Study on Combining Complementary and Contradictory Information in a Fuzzy-based System

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***Abstract*— In today's military environment large quantities of distinct information are available. In a time-constrained environment it is vital to have some way to judge the relative importance of information. Recent research has developed a fuzzy-based system to assign a Value of Information (VoI) determination for individual pieces of information. Subsequent work presented ideas for integrating complementary and/or contradictory information into the VoI process. This paper presents the results from experiments examining the idea of using complementary and/or contradictory new information to impact the previously used fuzzy membership values for the *information content* characteristic applied in the VoI calculations.**

Keywords—Information aggregation; information fusion; situational assessment; fuzzy associative memory; decision support system; intelligence analysis

I. INTRODUCTION

The amounts and types of data available within today's military environment are unparalleled. Military commanders and staffs have to not only overcome the usual information overload problem, but also deal with the perhaps more critical problem of deciding which information is the most important. This latter issue is exacerbated by the typical time constraints inherent in the military decision cycle. Calculating information importance, termed the value of information (VoI) metric, is a formidable task that is highly dependent upon its application to dynamic situations [1]. Solution flexibility is critical since VoI understanding must be readily applicable across a wide range of information types and military contexts.

The cognitive processes behind assigning a VoI assessment resist codification with exact precision and offer an excellent opportunity to leverage a computational intelligence solution using fuzzy inference. Fuzzy systems have been shown to be effective at approximate reasoning where information is uncertain, incomplete, imprecise, and/or vague [2,3,4,5,6]. Research over the past several years has been aimed at eliciting knowledge from military intelligence analyst Subject Matter Experts (SMEs) to understand how they perceive and evaluate the value of an *individual piece of information* [7]. From that work, a fuzzy-based VoI system has been developed using a Fuzzy Associative Memory (FAM) architecture [8, 9].

However, most complex decision-making processes, including those in the military, require the ability to integrate information not only from dissimilar sources, but also to combine new information with previous information. Complicating the latter issue is that new information may or may not agree with older information. A recent next step in the VoI research was to evaluate how military intelligence analysts reason when combining contradictory and/or complementary information and consider how to provide that capability in the VoI system [10]. This paper presents the results from empirical evaluation of the idea of using new information to impact the previously used fuzzy membership values for one of the characteristics applied in the VoI calculations.

The remainder of this paper is organized as follows: Section 2 presents background information related to information evaluation, the prototype VoI system, and strategies for handling data conflict. The empirical assessment, along with results, of our approach for using changes in the IC value of previous information to aggregate new information is presented in Section 3. Section 4 discusses conclusions and future work.

II. BACKGROUND

This section provides background information to motivate and understand the approach used in the methodology for combining complementary and/or contradictory information. First, the basic notion of rating individual pieces of information is explained from the military point of view. Next, the prototype fuzzy-based VoI system is briefly presented. Finally, various strategies for handling data conflict found in the literature are summarized and reviewed.

A. Information Evaluation

The only military regulatory guidance describing how to rate information is contained in the annex to NATO STANAG (Standard Agreement) 2022 as well as in Appendix B of US Army Field Manual FM-2-22.3 [11,12]. Each piece of information is to be judged by combining assessments based on the *reliability of the source* and its *information credibility or content*. The *reliability* value comes from the following range (high to low): reliable, usually reliable, fairly reliable, not usually reliable, unreliable, and cannot judge. The

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information content choices are as follows (high to low): confirmed, probably true, possibly true, doubtfully true, improbable, and cannot judge.

Note that there is no doctrinal guidance on how the composite ratings (e.g. *usually reliable / improbable*) are to be used or interpreted. Also, there is no detail on how such ratings are to be treated with respect to varied mission contexts. Further, it is easy to see that combining only information content and source reliability may not be enough to represent a reasonable "value of information". Discussions among the researchers and the military intelligence analyst SMEs led to the addition of *information timeliness* and *mission context* in the VoI determination process.

B. VoI System

It is interesting to note that the labels within the source reliability and information content domains are words, not numbers. These linguistic variables represent degrees of confidence and make fuzzy logic an appropriate choice for the VoI computations [13].

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 then 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.

In the current VoI system, three inputs are used: 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.

The overall architecture of the prototype fuzzy system is shown in Fig. 1. Instead of using one 3-dimentional FAM, two 2-dimensional FAMs were used. The reasoning behind this decision was presented in detail in [8] but essentially it provided a simpler knowledge elicitation process for the SMEs, decreased the total number of fuzzy rules, and provided a potential for the output of the first FAM to be useful on its own.

As seen in Fig. 1, two inputs feed into the *Applicability* FAM: source reliability (SR) and information content (IC); the output of the FAM is termed the information applicability decision. Likewise, two inputs feed into the *VoI* FAM: one of these (information applicability) is the output of the first FAM while the other input is the information timeliness value. The output of the second FAM, and the overall system output, is the VoI metric. Different mission contexts are represented by having multiple, automatically selected VoI FAMs.

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 [7].

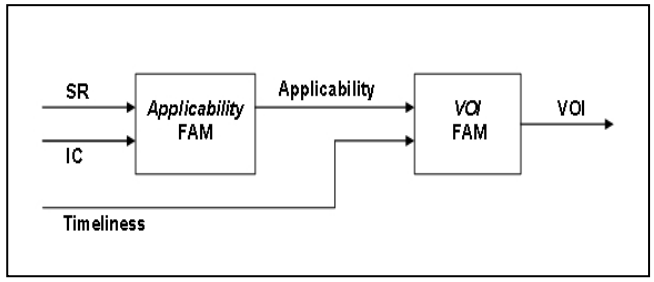

Fig. 1. VoI Prototype System Architecture

Within the Applicability FAM, the two input domains (source reliability and information content) are divided into five fuzzy sets following the guidance provided in [11]. The omission of the "cannot judge" category from both input domains is explained in [8]. Decomposition of the other domains was driven by the SMEs. The *timeliness* input domain was decomposed into three fuzzy sets (recent, somewhat recent, and old). The "information applicability" output domain was decomposed into nine fuzzy sets (ranging from *not applicable* to *extremely applicable*) while the VoI output domain utilized eleven fuzzy sets (ranging from *not valuable* to *extremely valuable*).

The decomposition of the *information content* domain into its five fuzzy sets is shown in Fig. 2. Each element in the domain has some grade of membership, from 0 to 1 inclusive, in each fuzzy set in the domain. The membership function determines the grade of membership; the shape of the fuzzy sets determines the membership function.

In Fig. 2, the membership value is shown on the y-axis and the values contained within the domain are shown on the x-axis (at the top). The illustrated decomposition requires the membership functions to be isosceles triangles with bases of the same width. The decompositions for all domains in the VoI system follow this requirement. Thus, any input within a domain will belong to at most two fuzzy sets; that is, any input will have non-zero membership in no more than two fuzzy sets. This means that, for each input, the antecedents for at most two fuzzy rules associated with that domain will be satisfied. Further, the sum for all membership values in the sets to which any input belongs will equal 1.

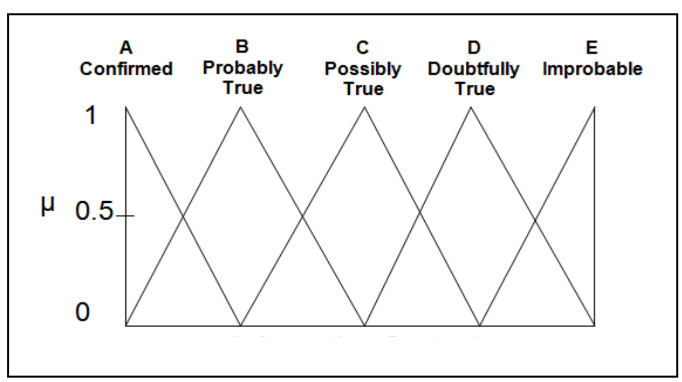

Fig. 2. *Information Content* Domain Decomposition

Note that, in general, the shape of the fuzzy sets in a fuzzy system does not have to be triangular as shown in Fig. 2. Also, the fuzzy sets decomposing a domain do not have to overlap in a regular pattern, nor does the sum have to be 1 for membership values for all sets in which an element is a member. Examination of other types of membership functions as applied to the VoI system can be found in [14, 15].

The output from the system is determined by the standard centroid defuzzification strategy. That is, the degree to which each rule influences the overall output is directly related to the degree to which its inputs match its antecedent fuzzy sets. However, following the above decomposition requirements for a 2-dimensional FAM structure, at most four fuzzy rules will have non-zero degrees (two rules will have "x" antecedents satisfied by input x and two rules will have "y" antecedents satisfied by input y; their intersection in the FAM defines the four fuzzy rules that should be "fired"). This aspect, plus the fact that the degrees for all rules will add to one, allows the decomposition structure to provide a computationally efficient defuzzification process.

More detailed descriptions of the FAMs, the fuzzy rule bases, the domain decompositions, and other implementation aspects of the system can be found in [9]. The series of surveys and interviews with SMEs that were used to integrate cognitive requirements, collect functional requirements, and elicit the fuzzy rules is presented in [7]. 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 SME expectations [16].

C. Data Conflict Strategies

While the VoI determinations produced by the prototype system have proved to be useful it is clear that the values will change over time. Simplistically, the VoI ratings will certainly change as time passes since *timeliness* is one of the input characteristics. But even beyond that it is obvious that the acquisition of new information could 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 and is the focus of this paper.

In the literature, the idea of having complementary or contradictory information is termed as 'data conflict' [17]. Handling data conflict has been an active research area in data fusion for many years; a survey in [17] provides a detailed classification of strategies to handle inconsistent data. Basically, three classes of strategies are presented: conflict ignorance, conflict avoidance, and conflict resolution.

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 [10] along with the reasons that none of these approaches or systems are well suited towards the military environment. To summarize, our problem does not allow us to use the strategies of 'conflict ignorance' or 'conflict avoidance'; the techniques present in the 'conflict resolution' class also do not fit our problem or environment.

Within the prototype VoI system the *information content* characteristic is concerned with whether a piece of information is complementary or contradictory relative to other information. The work presented in [10] talked about approaches for modifying the IC 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 Fig. 1 to find the new IC value that would be required to produce the new VoI determination. It is this approach that we empirically investigate and report on in this paper.

III. Empirical Study and Results

As implied in the preceding section, the investigation into using changes in the IC value of previous information to aggregate new information consisted of two basic parts. One facet was to examine the idea of "backwards solving" through the original VoI architecture to update the original IC value of an existing piece of information. The second aspect was a closer analysis of the results from a knowledge elicitation process designed to capture how the SMEs combine information.

A. Reverse FAM Examination

Recall that the number of fuzzy sets for the input and output domains of the FAMs in Fig. 1 are not all equal. That is, the *information content (IC)* and *source reliability (SR)* domains were each decomposed into 5 fuzzy sets; *timeliness* was separated into 3 fuzzy sets; the *applicability (APP)* domain was divided into 9 fuzzy sets; and the *VoI* domain used 11 fuzzy sets. It is obvious that this arrangement might cause some problems with the "backwards solving" process, so it is important to first take a look at how such a reverse FAM system might be structured.

To keep things simple it was decided to focus only on the Applicability FAM initially. That is, if it was assumed that timeliness and source reliability would remain constant between an instance of old and new information, the only deciding factor to get a new VoI rating would be a change in Applicability. Thus, with any necessary Applicability value known, the Applicability FAM could be "reversed" such that the inputs would be SR and Applicability, and the output would be the IC value required to reach the indicated new VoI rating.

The actual Applicability FAM for one of the mission contexts ('tactical') is shown in Table I. The *IC* fuzzy sets are labeled from 1 to 5, with 1 corresponding to the "best" value ('confirmed') and 5 corresponding to the "worst" value ('improbable'). Similarly, the *SR* fuzzy sets are labeled from

1 to 5, ranging from ‘reliable’ (best) to ‘unreliable’ (worst). The *APP* values shown in the cells of the FAM are read differently; that is, 9 represents the “best” value (‘extremely applicable’) and 1 represents the “worst” value (‘not applicable’). The inconsistency in whether the higher or lower number is best is a result of the doctrinal guidance for *SR* and *IC* clashing with the SME preferences for *APP*.

Recall that the FAM represents the fuzzy rules obtained from the SMEs. For example, the top, left cell in the FAM illustrated by Table I represents the rule: If *source reliability* is ‘reliable’ (*SR*=1) and *information content* is ‘confirmed’ (*IC*=1), then *applicability* is ‘extremely applicable’ (*APP*=9).

The reverse Applicability FAM using *APP* and *SR* as the inputs and *IC* as the output is shown in Table II. Note there are some cells with no values; these represent “holes” in the rule base. That is, there are *SR* and *APP* combinations for which no corresponding fuzzy rules were provided by the SMEs. For example, the top, left cell in the FAM illustrated by Table II depicts that the *IC* value for *SR*=1 and *APP*=1 is unknown or nonexistent. Put another way, the empty cell means that there is no output (or consequent) for the rule: If *source reliability* is ‘reliable’ (*SR*=1) and *applicability* is ‘not applicable’ (*APP*=1). Rephrasing yet again, this means the SMEs did not provide any *information content* value that would pair with SR=1 to produce an *applicability* value of 1.

B. Rule Base Completion

The absence of a defined output for rules in a rule-based system can be catastrophic. With that being the case, several methods for attempting to complete the rule base were examined to see if they might be able to provide reasonable, extrapolated rules in the places where there were none. These methods, and their results, are described in the next three sub-sections.

1) Rule Base Completion via Region Growing

The first completion technique to be examined follows the strategy of region growing commonly used in image segmentation [18]. In this method, empty cells that border nonempty cells are filled in by averaging the values in the neighboring cells. Thus, the process expands the regions in which values are present. The process must be iterated until the entire FAM is filled since the “growing” can only occur on the boundaries of filled regions.

Neighboring cells can be defined in multiple ways. For our purposes, in a two-dimensional FAM each cell not on the edge has four neighbors: up, down, left, and right. After computing a value for every nonempty cell having at least one nonempty neighbor, the values are inserted into the FAM and, if it is not complete, the growing process is repeated.

The result of performing region growing on the original reverse Applicability FAM is shown in Table III. The cells with no previous values have been filled in; thus, the rule base has been completed. That is, there are no potential fuzzy rules without a consequent. Closer examination of the FAM reveals some irregularities, however. For example, examine the row where *SR*=3 and look at the columns where *APP*=5 and 6 (circled cells). Notice that the *IC* value for *APP*=6 is higher than the IC value for *APP*=5. This claims that for a constant *SR*=3, the *IC* value has to be worse (drops from 1.5 to 2) to get a better *APP* (rises from 5 to 6). This is clearly counterintuitive and not in line with the reasoning process depicted by the SMEs in the initial fuzzy rules. Similar behavior is illustrated for the same *APP* values when *SR* equals 4 and 5.

The behavior is also illustrated in the color graph shown in Fig. 3. For the completed rule base to be “reasonable”, the colors shown in the color bar to the right should begin with the color associated with 5 (*IC*=5) in the top left hand corner of the graph, end up with the color associated with 1 (*IC*=1) in the bottom right hand corner, and have a somewhat linear flow in between. For the most part this happens; however, a pronounced vertical “dip” in color can be seen where *APP*=6 and *IC*=3, 4, and 5 (circled area).

TABLE I. APPLICABILITY FAM

Source Reliability \ Information Content	1	2	3	4	5
1	9	7	7	5	3
2	8	7	6	4	2
3	7	6	3	3	1
4	5	4	3	2	1
5	3	3	2	1	1

TABLE II. REVERSE APPLICABILITY FAM

Source Reliability \ Applicability	1	2	3	4	5	6	7	8	9
1			5		4		2.5		1
2		5		4		3	2	1	
3	5		3.5			2	1		
4	5	4	3	2	1				
5	4.5	3	1.5						

TABLE III. REVERSE APPLICABILITY FAM – REGION GROWING

Source Reliability \ Applicability	1	2	3	4	5	6	7	8	9
1	5	5	5	4.3	4	3.2	2.5	1.5	1
2	5	5	4.4	4	3.7	3	2	1	1
3	5	4.4	3.5	3.2	1.5	2	1	1	1
4	5	4	3	2	1	1.5	1	1	1
5	4.5	3	1.5	1.8	1	1.3	1.1	1	1

2) Rule Base Completion via Weighted Averaging

Rather than restrict the influences that determine the value of a cell in the FAM to the immediate neighbors, weighted averaging uses the values in the entire table to determine the value of an empty position. Completion using weighted averaging incorporates the influence of every rule into the construction of the remainder of the rule base [19].

The interpolative extensions of the rule base require a similarity measure to be applied to the values already in the FAM. For our purposes, in this two-dimensional table the standard Euclidean distance is used. Note that unlike region growing, weighted averaging completes the FAM in a single pass by using information from all the existing rules.

The result of performing weighted averaging on the original reverse Applicability FAM is shown in Table IV. As with region growing, the cells with no previous values have been filled in; thus, there are no potential fuzzy rules without a consequent. A close look at the result reveals significant anomalies. Table IV does not depict the expected somewhat linear transition from 5's in the top left hand corner of the FAM to 1's at the bottom right hand corner. The values now in the previously empty cells do not follow the expected structure. In fact, in all the rows of the FAM (each row represents a constant *SR* value) the values go up and down as they go from left to right, which is counterintuitive to the idea that better (lower) *IC* values are needed to reach better (higher) *APP* values. That is, the values going from left to right on any given row should remain equal or get smaller.

This behavior is dramatically illustrated in the color graph provided in Fig. 4. Instead of having a smooth transition from dark red at the top left hand corner to dark blue at the bottom right hand corner, the dark colors (indicating the *IC* value extremes) are scattered throughout the graph.

3) Rule Base Completion via Training Data

Traditionally, fuzzy rules have been derived by eliciting knowledge from SMEs; indeed, this is how the two FAMs in the VoI system were constructed. There are strategies, however, for learning fuzzy rules from training data. The notion behind learning fuzzy rules is that a set of training examples (input-output tuples) provide the information for the generation of the rules. The learning algorithm used here follows the well-known approach of Wang and Mendel [20].

To generate the training data for the Wang and Mendel algorithm, all possible *SR* and *IC* combinations from 1 to 5, in increments of 0.1, were used to generate their ensuing *APP* value. The result of this process was a list of 1681 {*SR*, *IC*, *APP*} tuples. This list was used as training data to generate fuzzy rules for the reverse Applicability FAM by using the *SR* and *APP* values as inputs, and the IC value as the output.

The result of using the generated training data to construct rules for the reverse Applicability FAM is shown in Table V. While the empty cells in the interior of the FAM have been filled in, the empty positions at the corners of the FAM remain; this is because the training data did not contain an example that could be used to construct a rule in the empty positions.

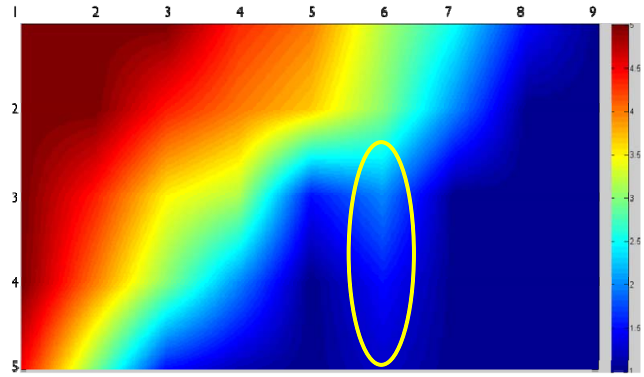

Fig. 3. Reverse Applicability FAM – Region Growing

TABLE IV. REVERSE APPLICABILITY FAM – WEIGHTED AVERAGING

Source Reliability \ Applicability	1	2	3	4	5	6	7	8	9
1	3.5	3.3	5	3.1	4	2.8	2.5	2.5	1
2	3.4	5	3.2	4	2.9	3	2	1	2.4
3	5	3.3	3.5	3.1	2.9	2	1	2.5	2.4
4	5	4	3	2	1	2.8	2.7	2.5	2.4
5	4.5	3	1.5	3	2.9	2.8	2.7	2.5	2.4

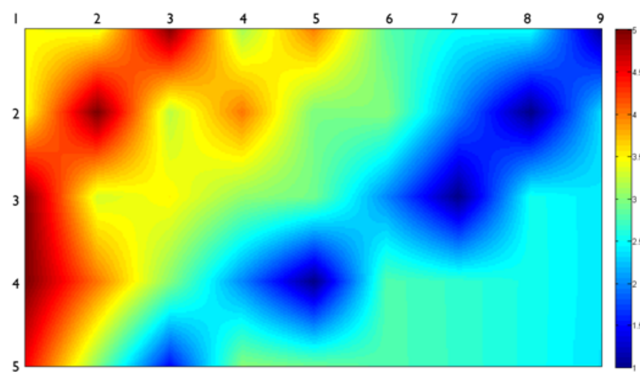

Fig. 4. Reverse Applicability FAM – Weighted Averaging

TABLE V. REVERSE APPLICABILITY FAM – TRAINING DATA

Source Reliability \ Applicability	1	2	3	4	5	6	7	8	9
1			5	4.5	4	3.5	2.5	1.5	1
2		5	4.5	4	3.5	3	2	1	
3	5	4.5	3.5	2.7	2.3	2	1		
4	5	4	3	2	1				
5	4.5	3	1.5						

A close examination of the empty cells shows that the resulting configuration is reasonable, both in terms of the values that were inserted in the previous empty cells and the cells that remain empty. For example, the empty cell where *SR*=1 and *APP*=1 means that there is no *SR*/*IC* combination that can produce an *APP* value of 1. Looking back to the original Applicability FAM (Table I) it can be seen that the lowest *APP* value in the top row (where *SR*=1) is 3; thus, it makes sense that no *SR*/*IC* combination can produce an *APP* value of 1. Similarly, it follows that the *SR*=1/*APP*=2 cell is empty as well (since the lowest *APP* value in the *SR*=1 row is 3). Analogous analysis of the remaining empty cells in Table V confirms the remaining results. Fig. 5 presents the associated color graph.

4) Rule Base Completion Summary

Clearly, none of the three rule base completion strategies is reasonable for our particular situation. While the region growing and weighted averaging methods fill in all the empty cells, the resulting fuzzy rules are not consistent with the reasoning process portrayed by the SMEs through the original Applicability FAM fuzzy rules. Rule base completion using training data produces reasonable rules for the FAM cells that got filled in, but there are still over 35% of the FAM rules missing. The conclusion is that rule base completion cannot be used to produce a reverse Applicability FAM that can model the way SMEs integrate complementary or contradictory information with previous information.

C. Reverse FAM Examination – Revisited

Up to this point the focus has been on obtaining appropriate rules for the empty cells in the reverse Applicability FAM. But what if the rules that are missing are not needed? That is, what if the reasoning by the SMEs to adjust the VoI when they combine two pieces of information does not depend on the missing rules? Perhaps the overall reasoning process for adjusting the old VoI value for a piece of information based on complementary or contradictory new information is consistent with the initial reasoning used for a single piece of information. In this case, the non-complete reverse Applicability FAM might be enough.

Concurrent with the research presented thus far, an experiment was ongoing to capture data about how the SMEs combine complementary and contradictory information in order to come up with the relevant situational understanding. In the exercise, four military intelligence analysts provided their opinions on the perceived change in VoI for 80 combinations of information. Various combinations of old *SR*/*IC* pairs along with new *SR*/*IC* pairs were presented, in addition to some indication of to what degree the new information was complementary or contradictory; the SMEs then provided their perceived change in VoI for the initial fact. More detail for this experiment can be found in [10].

While the above exercise was not designed specifically for the research in this paper, it turns out that some of the data were useful in deciding whether or not the partial reverse

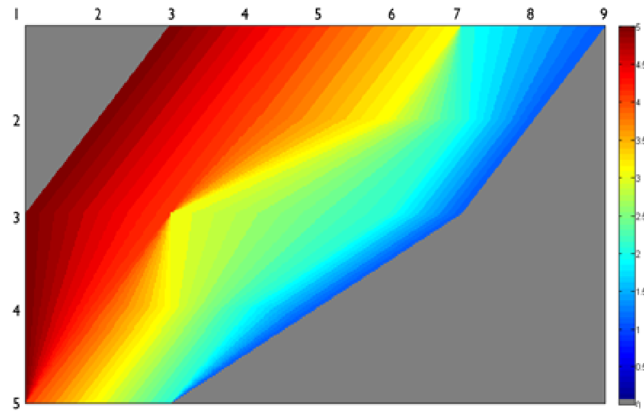

Fig. 5. Reverse Applicability FAM – Training Data

Applicability FAM was appropriate. The data were examined to investigate this issue.

First, examples of old/new *{SR,IC}* pairs were sought where the *SR* value did not change but the *IC* value did; this indicates an instance where the complementary or contradictory impact could be isolated to the *IC* characteristic, which is the representation we are seeking. It was quickly noticed that the partially empty reverse Applicability FAM would not suffice. As an example, one instance was as follows:

- Old: *SR*=2, *IC*=3;
- New: *SR*=2, *IC*=2;
- Timeliness and mission context did not change
- New information is 'totally complementary';
- Initial *VoI* for old fact = 5;
- Adjusted *VoI* for new fact = 7.5.

Given the particular mission context and timeliness value, to get to a *VoI* of 7.5, the *APP* value for *SR*=2, *IC*=3 would have to be 9. An examination of the partially empty reverse Applicability FAM (Table II) shows that the *SR*=2, *APP*=9 cell contains no entry. Also notice that the partially empty reverse Applicability FAM resulting from using training data (Table V) exhibits the same problem. That means there is no such *IC* value that could be used with *SR*=2 to produce an *APP* value of 9. Multiple other experimental combinations produced this same dilemma.

There was another anomaly that was noticed as well. In some combinations the SMEs came up with a resulting new *VoI* for the original information of 'extremely valuable' (the highest possible *VoI* value) or 'not valuable' (the lowest possible *VoI* value). In the initial VoI FAM for the associated mission context, there were no instances of fuzzy rules that produced either of those *VoI* values.

The above problems indicate that the partially complete reverse Applicability FAM cannot be used to model the way in which SMEs aggregate complementary or contradictory information with previous information.

D. Summary of Results

The empirical study into using changes to the IC value to aggregate new information examined three potential solution paths: "reversing" the Applicability FAM, using rule base completion, and then examining the reverse FAM from a different point of view.

The first technique of "reversing" the Applicability FAM consisted of using the *source reliability (SR)* and *applicability (App)* values as inputs and *information content (IC)* as the output; recall that the FAM was originally built with *SR* and *IC* being the inputs while *App* was the output. This "backwards solving" resulted in a FAM with empty cells; that is, there were possible input values for which no output was defined. This was considered to be an unacceptable result.

To try and fix the problem of undefined outputs, the next step was to examine a series of rule base completion processes to fill in the holes in the reversed FAM. Three approaches were tried: region growing, weighted averaging, and deriving rules from training data; unfortunately, none of the strategies resulted in a reasonable FAM. The region growing and weighted averaging methods did complete the empty cells in the FAM, but the resulting fuzzy rules were not consistent with the SME reasoning process illustrated by the original Applicability FAM rule base. While rule base completion using training data produced reasonable results for the cells that got filled in, over 35% of the FAM rules were still missing output values.

The final idea consisted of examining the reversed Applicability FAM to see if the missing rule outputs were actually needed. That is, perhaps the reasoning process used by the SMEs to combine two pieces of information would not need the incomplete rules; this would imply that the reasoning process to combine information is consistent with the initial reasoning used to evaluate a single piece of information. Regrettably, data from an experiment using the SMEs to aggregate complementary and contradictory information revealed that the reverse Applicability FAM (as well as the incomplete FAM that resulted from using the training data) was not sufficient to model the aggregation process.

IV. Conclusions and Future Work

Military intelligence analysts are inundated with information and must be able to judge which information is most important in a critical, uncertain, time-constrained environment. This dilemma prompted the recent development of a fuzzy-based Value of Information (VoI) system to assist in judging the value of individual pieces of information. A resulting issue was how to integrate new information with existing information given that the new information could be complementary or contradictory in nature. This paper presented the results from experiments and analysis examining the idea of using complementary and/or contradictory new information to impact the previously used fuzzy membership values for the *information content* (*IC*) characteristic applied in the VoI calculations.

The results from this work demonstrate that the simplistic update of the *IC* value for an old piece of information cannot model how our Subject Matter Experts (SMEs) aggregate complementary and contradictory information to create a new VoI determination. It is clear that the SMEs use a different reasoning process when new information is combined with old information. Despite our wishes otherwise, additional knowledge elicitation efforts are needed to construct fuzzy rules for a system to model the process of how VoI valuations are updated based on new information.

Future work will certainly involve the aforementioned additional knowledge elicitation endeavor. The merits of constructing a new FAM-based fuzzy system versus using some other fuzzy system architecture must be considered. How the new system for integrating multiple pieces of information will fit in with the current system for judging individual pieces of information will have to be studied as well. Other aspects must be deliberated, such as whether a system should be built to calculate VoI across multiple facts in real-time as needed, or if perhaps some "meta-fact" and its associated VoI should be created and stored to facilitate information evaluation.

Another approach to consider relates to recent work conducted under the administration of the Intelligence Advanced Research Projects Activity (IARPA) [21]. A past research program entitled Aggregative Contingent Estimation (ACE) [22] focused on developing methods for obtaining, evaluating, and aggregating the opinions of multiple experts. While much of this work appears to be aimed at knowledge elicitation activities, perhaps some of the approaches used in this area could be modified to combine multiple pieces of information with varying levels of agreement (complementary) and disagreement (contradictory). One concern with how the methods could be applied to our particular scenario revolves around the need to have the SMEs define conditional and/or joint probabilities. However, the work in [23] 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 work presented herein is an important step toward understanding how military intelligence analysts reason over and aggregate complementing and conflicting pieces of information to judge the value of such information. Recently, the VoI architecture has also been leveraged to develop a prototype system that provides alert priority ratings to aid computer network defense analysts [24]. More work is certainly needed, but these endeavors are critical to the goal of creating automated decision support tools to enhance military situational awareness.

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