

Capturing the Value of Information in Complex Military Environments

A Fuzzy-based Approach

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Abstract—Today's military operations require information from an unprecedented number of sources resulting in an overwhelming volume of collected data. A primary challenge for military commanders and their staff is separating the important information from the routine. Currently, the Value of Information (VOI) assigned a piece of information is a multiple step process requiring intelligence collectors and analysts to judge its value within a host of differing operational situations. The cognitive processes behind these conclusions resist codification with exact precision suggesting that new methodologies are required to deal with this significant issue. This paper presents an approach for calculating the VOI in complex military environments using a fuzzy associative memory model as an effective framework for contextually tuning the VOI based on the information's content, source reliability and latency

Keyword: Value of Information, Fuzzy Associative Memory, NATO Standard Agreement 2022 (Information Valuation)

I. INTRODUCTION

The nature of military operations has dramatically changed over the last several decades from an environment dominated by force-on-force kinetic combat to one that encompasses a full spectrum of military operations. Peacekeeping and humanitarian efforts have supplanted traditional combat operations as the single focus [1]. Challenging these efforts is an unprecedented increase in the types and amount of information available. From sophisticated unmanned ground acoustic sensors to open-source Really Simple Syndication (RSS) news feeds, the military commander and his staff are confounded not only by information overload, but more importantly with separating the important information from the routine. Calculating information importance, termed the value of information (VOI) metric, is a daunting task that is

highly dependent upon its application to dynamic situations and human judgment [2].

Currently the VOI assigned a piece of information is a multiple step process requiring intelligence collectors and analysts to judge its value within a host of differing operational situations. As such, the cognitive processes behind these conclusions resist codification with exact precision and offer an excellent opportunity to leverage a computational intelligent solution using fuzzy inference. Fuzzy systems have been shown to be effective at approximate reasoning where information is uncertain, incomplete, imprecise, and/or vague [3,4,5,6,7]. The situation surrounding the problem of VOI calculation makes the selection of fuzzy logic theory and constructs a suitable choice. In particular, the Fuzzy Associate Memory (FAM) architecture will be applied.

Toward that end, this paper presents an approach for assisting military analysts in managing the value of VOI in complex environments using a FAM model approach. In Section 2, background information on the military domain with respect to VOI is presented along with the knowledge elicitation process utilized to capture the fuzzy VOI rules. Outlined in Section 3 is the FAM approach utilized to codify the information content and source reliability along with information latency into a prototype for calculating VOI. The preliminary results are examined in Section 4 with the conclusions and the way ahead presented in Section 5

II. BACKGROUND

A. Understanding the Domain Challenge

On today's battlefield, information drives action. Commanders must know details about important persons, places and events within their area of operations to address issues ranging from kinetic fights to adjudicating legal disputes to revitalizing a depleted economy. While soldiers at the edge of conflict are one source that gathers data to support their mission, they are augmented by open sources (such as the internet and mass media), sensor data feeds, human intelligence and more. As depicted in Table 1, as the echelon

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increases, the scope of military operations and number of information reports grows tremendously. Intelligence analysts examine this information to determine the impact of trends, important human networks, and threat tactics, techniques, and procedures on current and future plans. But, as Major General Michael Flynn points out:

“At the battalion level and below, intelligence officers know a great deal about their local Afghan districts but are generally too understaffed to gather, store, disseminate, and digest the substantial body of crucial information that exists outside traditional intelligence channels.” [8]

Echelon	Planning time	Execution time	Reports per hour	Area of Operation
Division	Week	Week/Days	~Millions	Province
Brigade	Days	Days	170K	Province /district
Battalion	Days/hours	Day	56K	District
Company	Hours	Hours	18K	Village
Platoon	Hour/Min	Hour/Min	6K	Village/Hamlet

Table 1: Military Echelons with typical Operational Times / Areas [9]

As shown in Figure 1, accurate VOI estimation is essential to the intelligence analysis process, promoting improved situational understanding and effective decision making. Relevant intelligence information, that information with proper VOI, is integral to battlefield success. VOI is essential in the collect-assess portion of the intelligence process. At higher echelons, VOI is a metric useful in determining the degree of situational estimate accuracy amidst the uncertainty of combat. Additionally, VOI is a focusing element as a searchable criterion, enabling analysts to find relevant information quickly. At lower echelons, analysts can use VOI to create an optimum course of action for immediate mission execution.

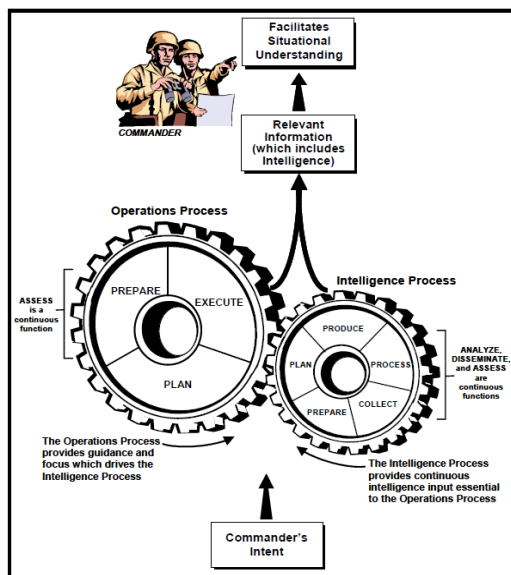


Figure 1: Military Information Process [10]

B. Information Valuation

The annex to NATO STANAG (Standard Agreement) 2022 along with Appendix B of US Army FM-2-22.3 essentially describe the same procedure for alphanumerically rating the “confidence” or “applicability” assigned a piece of information. The NATO standard further dictates that where possible “an evaluation of each separate item of information included in an intelligence report, and not merely the report as a whole” should be made [11]. The valuation of each piece of information is based on the combined assessment of the *reliability of the source* of the information with the assessment of its *information credibility or content*. Outlined in Table 2 and Table 3, respectively, the alphabetic Reliability scale ranges from A (Completely Reliable) to E (Unreliable) while the numeric Content scale ranges from 1 (Confirmed by other sources) to 5 (Improbable) [10, 11]. Both scales account for the information that cannot be judged for source reliability or content with ratings F and 6.

So as an example, a piece of information that was received by a source that has in the past provided *valid* information would be scored a *Reliability Rating* of either B or C; depending on the degree of doubt in authenticity. That same piece of information, if not confirmed, but seeming logical, would receive a *Content Rating* of either 2 or 3; again depending on the degree the information was consistent with other information. It is obvious that the subjective nature of the ratings (B2 vs. C3) can quickly lead to ambiguity. Required is a system that can effectively manage vagueness and uncertainty – a fuzzy-based approach.

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 Judge	No basis exists for evaluating the reliability of the source

Table 2: Source Reliability [10]

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 Judge	No basis exists for evaluating the validity of the information

Table 3: Information Content [10]

In an attempt to guide the application of composite ratings (i.e., B2 vs. E3) to varied operational situations, organizations have generalized the usefulness of data by developing charts similar to the one shown in Figure 2 [12]. Positioned along the x-axis are the possible ratings for source reliability while the y-axis reflects the possible ratings for information content. Combined, these ratings form a composite, or *applicability rating*, that in general reflects the applicability of a piece of information to analysis efforts. In Figure 2, a piece of information can have three distinct applicability states, namely black is good, grey is questionable, and white is not useable. This rudimentary attempt to form a composite value shows progress, but the three states encompass too many combined categories for a detailed understanding of VOI.

	A	B	C	D	E	F
1						
2						
3						
4						
5						
6						

Figure 2: Example Information Source / Reliability Matrix

C. Knowledge Elicitation to Refine VOI Process

In general military operations are defined by their associated *operation tempo*; that is, the time it takes to plan, prepare and execute an exercise. High-tempo operations typically require the decision cycle to be measured in minutes to hours, while slower tempo operations will generally allow the decision cycle to be measured in months or longer. Absent from the model above is the combination of the *information applicability* rating with a specific operation type. Without the specific framework of a given operations tempo the associated impact of information latency (or information timeliness) requirements are lost. Restated, true VOI is dependent upon the type of military operation to which the information is being applied. For instance, in a high-tempo operation, where decisions are made in short timeframes, added emphasis is assigned to information that has high applicability and was more recently received than others.

In order to capture the cognitive requirements necessary to refine the model and build the associated fuzzy association rules, a two-part Likert survey was proffered. As shown in Figure 3, the first step included surveying a group of subject matter experts (SMEs) to redefine the *information applicability* ratings based on a scale from 1 (Not Applicable) to 9 (Extremely Applicable). For this prototype, the respective

ratings for ‘cannot be judged’ that are associated with the ratings F and 6 were excluded. Using the results from the newly derived Information Applicability Table, the second step involved surveying the SMEs to assign a Likert scale from 0 – 10 for the VOI for a high-tempo military operation, as shown in Figure 4. For this step the definition of recent, somewhat recent and old were left for SME interpretation. The results of the surveys were reviewed as a collective group with the SMEs with the averages used to create the fuzzy rule set.

Information Applicability Matrix		Information Content					Likert Scale	
		IC	1	2	3	4		
Source Reliability	SR							9 Extremely Applicable
	A							8
	B							7 Highly Applicable
	C							6
	D							5 Moderately Applicable
	E							4
								3 Somewhat Applicable
								2
								1 Not Applicable

Figure 3: Likert Survey for Refined Information Applicability

Value Of Information Matrix		Information Latency wrt High-Tempo Operation			Likert Scale
		Recent	Somewhat Recent	Old	
Refined Information Applicability	IA \ TA				
	9				10 Extremely Valuable
	8				9
	7				8 Highly Valuable
	6				7
	5				6 Moderately Valuable
	4				5
	3				4 Somewhat Valuable
	2				3
	1				2 Minimally Valuable
				1	
				0 Not Valuable	

Figure 4: Likert Survey for High-Tempo VIO

III. APPROACH

The Fuzzy Associative Memory (FAM) model was chosen to construct the prototype fuzzy system. A FAM is a k -dimensional table where each dimension corresponds to one of the input universes of the rules. The i th dimension of the table is indexed by the fuzzy sets that compromise the

decomposition of the i th input domain. For the prototype system, three inputs are used to make the VOI decision (source reliability, information content, and timeliness); with three input domains, a 3-dimensional FAM could be used. However, the decision was made to use two, 2-dimensional FAMs connected “in series” to produce the overall VOI result. This choice will be addressed in more detail later.

The remainder of this section presents the overall architecture of the prototype fuzzy VOI system, the structure and content of the fuzzy rules bases, and the rationale for using two 2-dimensional FAMs versus one 3-dimensional FAM.

A. Prototype Architecture

The overall architecture of the prototype fuzzy system is shown in Figure 5. Two inputs feed into the *Applicability* FAM: source reliability and information content; the output of the FAM is the information applicability decision. Likewise, two inputs feed into the *VOI* FAM: one of these (information applicability) is the output of the first FAM; the other input is the information timeliness rating. The output of the second FAM, and the overall system output, is the VOI metric.

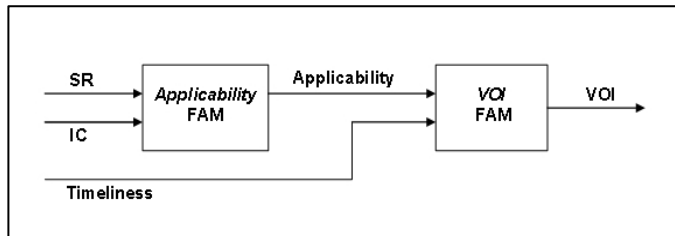


Figure 5: Prototype System Architecture

B. Fuzzy Rule Base

The first step in the design of a fuzzy inference system is to decompose the input and output domains into fuzzy sets. The decomposition defines the terms that may appear in the antecedents and consequents of the fuzzy rules, thereby determining the language of the rule base. Essentially, the number of fuzzy sets (and the “language” of the rule base) was defined in the knowledge elicitation phase discussed above. That is, the decomposition of the domains is as shown in Figures 3 and 4. For the *Applicability* FAM, the two input domains (source reliability and information content) are divided into five fuzzy sets; the output domain (information applicability) is divided into nine fuzzy sets. Similarly, for the *VOI* FAM, the input domain for information applicability uses nine fuzzy sets, the timeliness input domain three fuzzy sets, and the VOI output domain eleven fuzzy sets.

The “shape” of the fuzzy sets defines the membership functions for the system. While there are numerous shapes for fuzzy sets (triangular, trapezoidal, and the like), triangular membership functions are used in the prototype system to facilitate the inference calculations. Further, the inference process is made even more efficient by requiring the

membership functions to be isosceles triangles with bases of the same width; this triangular decomposition with evenly spaced midpoints has been referred to as a TPE system [13].

As an example, Figure 6 illustrates the decomposition of the source reliability input domain into five fuzzy sets. It is easy to see that the TPE restriction ensures that any input within the 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. Each of the other four domains is similarly decomposed into the appropriate number of fuzzy sets per the previous discussion, also using the TPE structure.

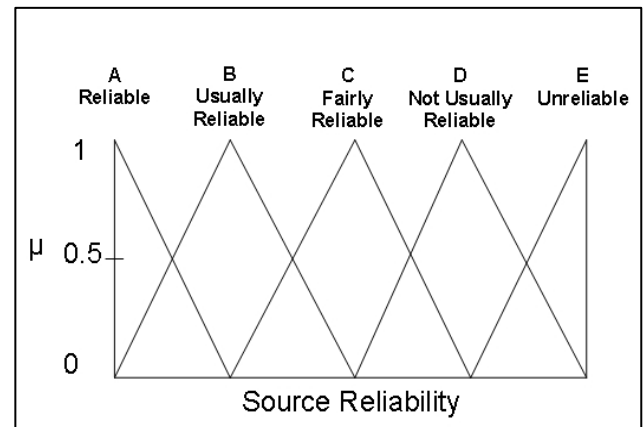


Figure 6: Decomposition of the “Source Reliability” Domain

Figure 7 depicts the rule bases for the two FAMs resulting from the information provided by the SMEs during the knowledge elicitation process. The shading is used as in Figure 2 to graphically indicate the “rating” of the output value in the cells, going from black (good) to not useable (white). The row and column indices of each FAM define a potential rule antecedent within the appropriate input domain. The number in each cell represents the consequent value of the rule that is represented by the cell indices. For example, one rule in the *Applicability* FAM is “If *source reliability* is B (usually reliable) and *Information Content* is 2 (probably true), then *Information Applicability* is 7 (highly applicable)”.

Notice that the values in the cells of the *VOI* FAM do not necessarily correspond exactly to the numbers 0 -10 used in the Likert scale by the SMEs to rate the VOI. For example, the *VOI* FAM contains the rule: “If *information applicability* is 5 (moderately applicable) and *timeliness* is somewhat recent, then *VOI* is 2.67”. The value of 2.67 is two-thirds higher than “minimally valuable” but a one-third less than a VOI of 3 (which is halfway between “minimally valuable” and “somewhat valuable”). Whether the format of the output should be a raw number or some sort of linguistic determination is an issue yet to be decided by the SMEs; the prototype system can easily be made to provide either form.

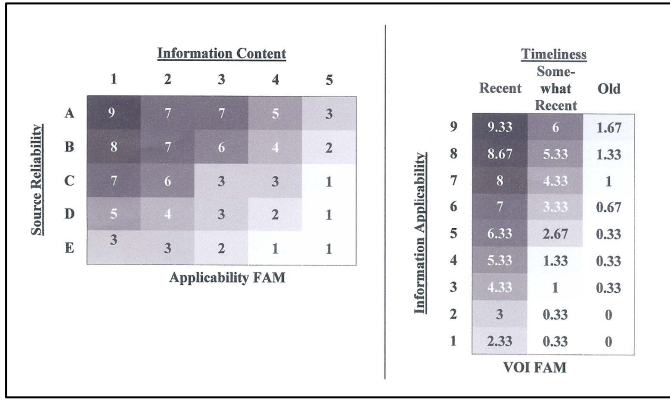


Figure 7: Prototype System Rule Bases

C. 2D versus 3D FAM

As mentioned earlier, with three inputs used for the overall VOI determination, it would have been possible to construct one 3-dimensional FAM instead of using two 2-dimensional FAMs. The choice to use the two smaller-dimension FAMs was made for several reasons.

First, each FAM directly corresponds to one of the steps in the knowledge elicitation process. Using only 2-dimensional “questions” provided a much simpler process for the SMEs to provide the rules. Additionally, the 2-dimensional environment allows the SMEs to more easily see how the inputs (and rules) work together to produce the overall system output. Thus, this not only adds confidence in the system but also allows for the “tweaking” of the rules by the SMEs.

Another reason for the two 2-dimensional FAMs is that the total number of rules is about one-third less than what would be required for a 3-dimensional FAM. In the two, 2D system there is a total of 52 rules (25 in the *Applicability* FAM and 27 in the *VOI* FAM. For a single 3-D FAM with the same domain decompositions, $5 \times 5 \times 3 = 75$ rules would be needed.

Perhaps the most compelling reason to use the two 2D FAMs is that the output from the *Applicability* FAM is potentially useful on its own. While the conceptual view of the system architecture shown in Figure 5 implies that the system is used to take three inputs and immediately produce the VOI of the piece of information, this need not be the case. Recall that it was mentioned that VOI actually depends on the type of military operation to which the information is being applied; that is, the operation “tempo” provides the context for how to judge the information value. However, information is steadily being accumulated even when no specific military operation is currently underway. Thus, the *applicability* of the information could be judged, but no determination could be reasonably made about the information *value*. Consider the scenario in which each incoming piece of information is timestamped, marked with its applicability metric, and then stored in a database for future use. As a military operation (or even multiple operations with potentially different tempos) commence, the individual pieces of information can be pulled from the database, judged for timeliness based on the recorded

timestamp, and then be processed for value based on the applicability and timeliness measures. In this view, the operation of the *applicability* FAM could be seen as “preprocessing” of the information, thereby speeding up the VOI determination when the information is actually needed for decision making within a specific context.

IV. PRELIMINARY RESULTS

The prototype system has been exercised across numerous scenarios (that is, various combinations of input values) to produce VOI determinations. While the preliminary results have not been formally validated by the SMEs in a structured way, informal evaluation has provided confidence in the output of the system. The system performance will need to be validated by providing the SMEs with various scenario-based VOI results for their examination and feedback. In some cases the output of the system is an exact application of the rules provided by the SMEs which should permit easy judgment; in other instances, the system output is less clear.

Looking at Figure 7, it is obvious that if the inputs exactly match the indices of the FAMs the VOI calculation is a simple, albeit automated, table-lookup operation. For example, if source reliability is “C” and information content is “3” and timeliness is “recent”, then the VOI is easily determined to be 4.33; no mathematical calculations are required. Note that the value of using fuzzy sets in this case is strictly limited to the ability to use linguistic variables (potential rule antecedents and consequents) in the knowledge elicitation process; however, this capability is integral to the construction of such a VOI system and should not be considered trivial in any sense.

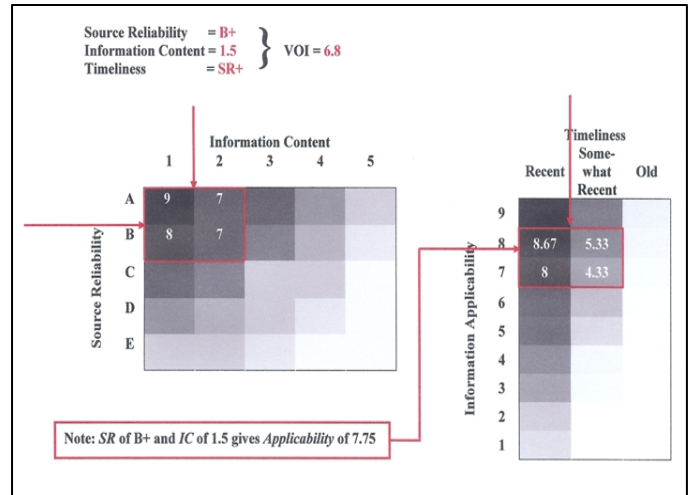


Figure 8: Example VOI Calculation

The more standard contribution from fuzzy sets is illustrated when the input values do not exactly match the indices of the FAMs. For example, consider the situation illustrated by Figure 8. In this case, the analyst received a piece of information for which the source reliability was judged to be halfway between A and B (denoted by B+);

likewise, information content was assigned a value of 1.5 (halfway between 1 and 2). So, the source reliability input matches the antecedents of two fuzzy rules by having partial membership in fuzzy sets “A” and “B”. Similarly, the information content input has partial membership in fuzzy sets “1” and “2”. Note that this will cause four fuzzy rules in the FAM to “fire” (in a TPE system with two inputs, this is the maximum number of rules that can be matched for any given input set).

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 for *information applicability* is directly related to the degree to which its inputs match its antecedent fuzzy sets. For example, the source reliability input matches fuzzy set “A” to degree .5 and the information content input matches fuzzy set “1” to degree .5; the weight of this rule is calculated as $.5 \times .5 = .25$. The output for the rule (“9”) is scaled by the degree to which the antecedents were matched, giving $9 \times .25 = 2.25$ as the contribution of this rule towards the *information applicability* value. Since all antecedents are matched by .5, it is easy to determine the values produced by the other three rules: $[A,2] = .25 \times 7 = 1.75$; $[B,1] = .25 \times 8 = 2$; and $[B,2] = .25 \times 7 = 1.75$. Summing all these values ($2.25 + 1.75 + 2 + 1.75 = 7.75$) and dividing by the sum of the weights of all the rules ($.25 + .25 + .25 + .25 = 1$) gives an *information applicability* value of 7.75. Note that in a TPE system the summation of the weights for all “fired” rules will always be 1, so the final division operation is not required.

The *information applicability* output value of 7.75 is then used as one of the inputs to the *VOI* FAM; in this case the “timeliness” input has been judged by some analyst to be halfway between “recent” and “somewhat recent” (denoted by SR+). The centroid defuzzification method produces an output of 6.8 in this case, which is the overall *VOI* value.

Other interesting results have been achieved in the course of eliciting knowledge from the SMEs and constructing the prototype system. For example, one way the system could be employed by analysts is to produce a *VOI* for each piece of information, thereby allowing prioritization of information to aid in deciding what to look at first. However, in the case of an extremely fast tempo operation where information overload is a significant obstacle, it might be more useful to use the system to stop less valuable information from even being passed to decision makers. In this case, the system could be enhanced so that a *VOI* threshold could be set allowing only information meeting or exceeding the threshold to be forwarded for consideration. By employing the FAM architecture, analysts can have an idea of how particular thresholds might influence the types and amount of information that gets culled. For example, by examining the *VOI* FAM in Figure 7, it is clear that if a *VOI* threshold of, say 8 (or its linguistic equivalent), is set that only information with *applicability* of 7 or greater AND with *timeliness* of recent

would meet this level. Similar inspection of the *Applicability* FAM reveals that there are only 6 combinations of source reliability and information content that produce an *applicability* value of 7 or greater.

V. CONCLUSION AND WAY FORWARD

Calculating the value of a piece of information in today’s military environment is a daunting task, dependent upon human judgment and a multiple step process requiring intelligence collectors and analysts to make decisions within a host of differing operational situations. The cognitive processes behind these conclusions resist codification with exact precision, leading to the application of a computational intelligent solution using fuzzy inference. Toward that end, this paper presents the development of a prototype system which uses a fuzzy associative memory model to provide an effective framework for determining the *VOI* based on the information’s content, source reliability and latency.

The obvious next step for this effort is to seek validation of the system from the SMEs by producing various scenario-based *VOI* results for their examination and feedback. While it is hoped that the SMEs will agree with the *VOI* determinations from the prototype system, it is entirely possible that the system will require some adjustment. Perhaps after seeing the FAMs, how they interact, and the system outputs, the SMEs might revise some of their decisions causing the rule base to be modified.

Although the prototype system only considers a high-tempo operation, rules were elicited from the SMEs for medium and slow tempo operations as well. The system will need to be enhanced to include multiple *VOI* rule bases so that users may easily define the operation tempo under consideration, causing the appropriate rule base to be selected automatically.

There are numerous augmentations that can be made through a sophisticated graphical user interface. One example could be the addition of a capability for the analyst to simply click somewhere in the ranges for the inputs to indicate their values. For example, the user could be presented with a “picture” of the source reliability domain and be instructed to click along the range to select the appropriate value for a piece of information. This would allow the input values to be more “analog” in nature and perhaps make the determination process more efficient and accurate. The concept of a “fuzzy Z-mouse” proposed by Zadeh could also be used [14]. Such a tool would allow users to provide their perceptions of input values with a “spray can” instrument; this provides a method of gathering “fuzzy” perceptions instead of forcing a single point value to be provided.

It is clear that various scenario-based experiments with a collection of users will have to be conducted to receive feedback for improving and validating the system, both in its prototype stage and as it is enhanced. It is likely that additional factors will need to be used to compute *VOI*.

Considerations such as uncertainty, imprecision, inconsistency and others will need to be investigated.

Providing commanders and analysts with software tools to assist in a finer determination of VOI and the capability to more quickly examine increasing amount of disparate information holds the potential for quickly generating useful intelligence at all echelons. In today's complex, time-sensitive, context-dependent military environments this ability is critical. For the military, the ability to efficiently and effectively calculate VOI and separate the wheat from the chaff is paramount. While this proof-of-concept prototype system is only the beginning, it is an important step towards that goal.

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