Voting and Choquet Fusion – A System-of-Systems Error Resilient Comparison

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Abstract

The concept of modeling multiple complex adaptive systems (CAS) as if they were voting processes proposes that an Error Resilient Data Fusion (ERDF) method can help to mitigate the effects of emergent properties in CAS system-of-systems (SoS). The property of *emergence* in a CAS composed of multiple, multi-modal sensors poses specific problems for fusion processes due to the difficulty in predicting and accounting for sensor performance under disparate environmental conditions. This paper compares the voting and Choquet integral fusion methods in the context of a multi-modal sensor ERDF SoS.

Background of ERCO Needs

One characteristic of a Complex Adaptive System (CAS) is the property of *emergence*. Emergence, from a system-of-systems (SoS) perspective, is the characteristic that interactions between systems result in properties and behaviors that are not characteristic of either system independently. One application is the fusion of information from disparate sensor systems that contribute to military situational awareness (SA) capabilities for tactical decision-making purposes (Schuck and Blasch 2010). Other examples include managing error in wireless sensor fusion systems (Urken 2005) and detecting the stability of a shared feeder line via a series of cooperative, interconnected power microgrids (Urken 2010).

In these types of distributed SoS, information fusion is often desired in order to optimize decision-making with incomplete and imperfect information. Error-resilient collective outcome (ERCO) methods are also desired due to the need to minimize the effects of invalid and corrupted data from diverse sensors and sources. This is especially true for data and information that may be intentionally modified or denied due to hostile agents. In tactical military systems, this is assumed as part of the underlying basis of operations.

Two error-resilient data fusion (ERDF) methods that can support ERCO SoS are described in this paper. The first is a voting methodology described by Urken (2005). The second is a methodology based on a Choquet Integral method described by Warren (1999) and extended by Schuck and Blasch (2010).

Description of ERCO Systems-of-Systems

Referencing the wireless ERCO work by Urken (2005), the author develops the concept of an ERCO voting method for complex decision tasks in realistic networked systems where information may be unreported or distorted.

As an example, the US Army might distribute hundreds of unattended ground sensors (UGS) in a small region that are multi-modal (seismic, acoustic, magnetic, etc.)[1]. These could be damaged in the course of their operational life, placed in various soil conditions that may not allow realization of full sensor capabilities, or be located too close to a source of interference, such as a gasoline

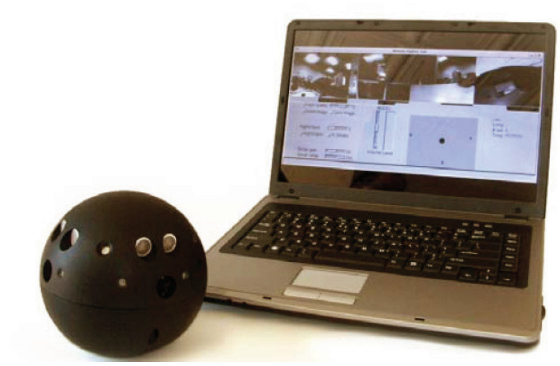

Figure 1 – Mobile Fusion Scout Ball™ and Monitor

[1] http://defense-update.com/features/du-1-06/feature-ugs.htm

powered generator. Indoor monitoring harbors similar types of problems as might be encountered by a network of MobileFusion Scout Balls™ as seen in figure 1[2]. Monitoring of National Park resources also has similar types of problems (Shepherd and Kumar 2005; Xu no date).

Voting Fusion and ERCOs

Urken (2005) sets up a scenario where two types of sensors (AC – acoustic and IR – infrared) independently report their "best guess" hypotheses of the number of vehicles in a convoy (0 – 4) with probabilities scaled from 0 (not possible) to 10 (certain probability). These can be distributed across the hypothesis space and each sensor must completely distribute all its votes. Table 1 is captured from Urken (2005) and it shows the sensor outputs from this hypothetical system for one moment in time.

Table 1 – Convoy Vehicle Assessment Sensor Ratings

No. of Vehicles	0	1	2	3	4
Sensors and Ratings					
AC1	0	5	4	1	0
AC2	0	10	0	0	0
AC3	0	5	3	1	1
AC4	0	1	6	3	0
AC5	0	3	5	2	0
AC6	0	1	8	1	0
IR1	0	0	0	4	6
IR2	0	0	0	2	8
IR3	0	0	1	3	6
IR4	0	0	1	2	7

From table 1, it can be seen that each sensor distributed its votes in different ways to communicate its judgments about the attributes of the convoy. Sensor AC2 placed all of its votes that one vehicle comprises the convoy, while the rest of the acoustic sensors had various distributions between one and four vehicles. The IR sensors provided a much different distribution of votes. These differences could reflect real-world problems such as geometry limitations, blind spots, and sensor limitations with respect to target classes (such as vehicles with IR coverings and hidden heat sources).

Following a one person-one vote (OPOV) rule, for every majority winner (minimum 5 out of 10 votes), the following results are shown in table 2 (Urken 2005).

Table 2 – OPOV Allocations for Convoy Assessment

No. of Vehicles	0	1	2	3	4
Allocation of Votes					
AC1	0	1	0	0	0
AC2	0	1	0	0	0
AC3	0	1	0	0	0
AC4	0	0	1	0	0
AC5	0	0	1	0	0
AC6	0	0	1	0	0
IR1	0	0	0	0	1
IR2	0	0	0	0	1
IR3	0	0	0	0	1
IR4	0	0	0	0	1

The results of table 2 are intuitive, but do not help in decision-making. What is needed is the set of sensor confidence values to include in the calculations. Again referencing Urken (2005), if the probability of correct choice p is assessed as 0.2 for AC1-AC3, 0.5 for AC4-AC6, and 0.8 for IR1-IR4 and these values are transformed into weights via the Shapley-Grofman theorem, the data in tables 1 and 2 provide the results shown in table 3.

Table 3 – Sensor Allocations after Shapley-Grofman Weighting

No. of Vehicles	0	1	2	3	4
Sensors and Ratings					
AC1 (0.2)	0	-1.39	0	0	0
AC2 (0.2)	0	-1.39	0	0	0
AC3 (0.2)	0	-1.39	0	0	0
AC4 (0.5)	0	0	0	0	0
AC5 (0.5)	0	0	0	0	0
AC6 (0.5)	0	0	0	0	0
IR1 (0.8)	0	0	0	0	1.39
IR2 (0.8)	0	0	0	0	1.39
IR3 (0.8)	0	0	0	0	1.39
IR4 (0.8)	0	0	0	0	1.39
Vote Totals	0	-4.17	0	0	5.56

[2] http://www.mobilefusioninc.com/index.html

Additionally, Urken (2005) provides the following ERCO example for missing data from AC2 and AC6 in table 4. Based on the sensor confidence values and the Shapley-Grofman weights, the result of "4 vehicles" will be an ERCO. By inspection, this would be the same result even if additional sensors cease reporting.

Table 4 – ERCO Voting Results from Missing Sensor Data

No. of Vehicles / Sensors and Ratings	0	1	2	3	4
AC1 (0.2)	0	-1.39	0	0	0
AC2 (0.2)	Missing Data				
AC3 (0.2)	0	-1.39	0	0	0
AC4 (0.5)	0	0	0	0	0
AC5 (0.5)	0	0	0	0	0
AC6 (0.5)	Missing Data				
IR1 (0.8)	0	0	0	0	1.39
IR2 (0.8)	0	0	0	0	1.39
IR3 (0.8)	0	0	0	0	1.39
IR4 (0.8)	0	0	0	0	1.39
Vote Totals	0	-2.78	0	0	5.56

Choquet Fusion and ERCO

From Schuck and Blasch (2010), there is an approach to mimic human cognition and decision-making using the Choquet integral for the purpose of knowledge generation – i.e. higher order fusion. The Choquet integral is a non-additive, fuzzy-like integral where subsets of information are aggregated, which enables inter-element associations and non-linearities to be captured. For the purpose of establishing an ERCO, the results of the Choquet integral process will be used in the analysis in this paper without an automated risk-based assessment. For automated decision-making using the Choquet integral, Schuck and Blasch (2010) propose that the statistics of the Choquet integral can be used to establish a human decision-maker's certainty equivalent (CE), based on utility theory, where a risk tolerance is provided and an equivalent human decision based on a Bayesian risk assessment can be calculated.

The Choquet-based data relationship is built upon by Sugeno (1974) where for the subsets A and B with $A \cap B = \phi$:

$$g(A \cup B) = g(A) + g(B) + \lambda\, g(A)\, g(B) \qquad (1)$$

Where g is the Sugeno measure (also referred to as a density) and λ is a constant on the interval [-1, ∞] that defines the additivity of the subsets, and is a probability measure when equal to 0 (Gader et al. 2004).

According to Klir (2006), the Choquet integral is a kind of monotone measure, μ, on the ordered pair [X, C] where X is the universal set and C is the nonempty family of subsets X. The Choquet integral is denoted as $\mu: C \rightarrow [0, \infty]$ and satisfies for all $A, B \in C$, if $A \subseteq B$, then $\mu(A) \leq \mu(B)$ (monotonicity).

If $\mu(A \cup B)$ is either $\geq$ or $\leq$ $\mu(A) + \mu(B)$ $\forall\, A \cup B \in C$ such that $A \cap B = \phi$, then the monotone measure is called superadditive or subadditive respectively and its characteristics are expanded in the following way (Klir 2006 and Grabisch 2000).

a) $\mu(A \cup B) > \mu(A) + \mu(B)$ synergy/cooperation between *A* and *B* where the importance of *A* and *B* together is greater than the sum of the individual importances – this is superadditivity)
b) $\mu(A \cup B) = \mu(A) + \mu(B)$ (*A* and *B* are non-interactive and thus independent)
c) $\mu(A \cup B) < \mu(A) + \mu(B)$ (incompatibility between *A* and *B* where the importance of *A* and *B* together is less than the sum of the individual importances – this is subadditivity)

Klir (2006) further states that classical probability theory can only capture (b); otherwise, the axiom of additivity is violated. Thus the theory of monotone measures like the Choquet integral provides a rich framework for capturing and formalizing uncertainty. The discrete Choquet integral (C(•)) is defined by Warren (1999) as:

$$C(\bullet) = \sum_{i=1}^{n} \left(\mu(A_i) - \mu(A_{i-1})\right) f(x_i) \qquad (2)$$

Where,

$$\lambda + 1 = \prod_{i=1}^{n} (1 + w_i \lambda) \qquad (3)$$

$$\mu(A_i) = \mu(A_{i-1}) + w_i + \lambda w_i \mu(A_{i-1}) \qquad (4)$$

With w_i = the individual information weights, $\mu(A_i)$ = the monotone subset weight (where $\mu(A_0) = 0$), λ = the non-additive parameter in the Sugeno equation, and $f(x)$ is the global value estimate (provided by the sensor votes).

Mapping the Choquet Integral to ERCO Example

The Choquet integral approach can be mapped to the example ERCO by Urken (2005). For this example, the votes from each sensor are scaled from 0 to 100 (instead of 0 to 10), are averaged for each sensor group and are assigned to each $\mu(A_i)$, applied to the sensor confidence weights of 0.2, 0.5, and 0.8 respectively and assigned to w_i. The table 1 equivalent assignments and table 3 equivalent results are shown in table 5.

Table 5 – Choquet Convoy Assessment Results

No. of Vehicles-$u(A_i)$	0	1	2	3	4
Sensors and Ratings					
AC1-3 (w=0.2)	0	66.7	23.3	6.7	3.3
AC4-6 (w=0.5)	0	16.7	63.3	20	0
IR1-4 (w=0.8)	0	0	10	27.5	67.5
Results					
Choquet Value	0	20.3	38.2	25.5	54.2
Weight Ave of $u(A_i)$	0	27.8	32.2	18.1	23.6
Omega	0	-7.5	5.9	7.4	30.6

The Omega value (Warren 1999) is simply the Choquet calculations minus the weighted average of each $\mu(A_i)$. The Choquet integral has been described as a "distorted average", so the Omega value provides a glimpse of the effects of the resultant sub/superadditivity.

The Choquet results are very similar to the voting results in table 3. For the ERCO case in table 4, the following results are obtained in table 6 for the Choquet case. Here missing data is not considered an output, so the "non-data" from sensors AC2 and AC6 are not included.

Table 6 – Choquet ERCO with Missing Data for AC2 & AC6

No. of Vehicles-$u(A_i)$	0	1	2	3	4
Sensors and Ratings					
AC1-3 (w=0.2)	0	50	35	10	5
AC4-6 (w=0.5)	0	20	55	25	0
IR1-4 (w=0.8)	0	0	10	27.5	67.5
Results					
Choquet Value	0	18.3	35.4	26.4	54.3
Weight Ave of $u(A_i)$	0	23.3	33.3	20.8	24.2
Omega	0	-5.0	2.1	5.6	30.2

Again, the results of the Choquet ERCO in table 6 are similar to those for the voting ERCO in table 4.

Looking again at the original work by Urken (2005), one can also see other possible scenarios. For example, if the missing data from sensors AC2 and AC6 were instead actual responses of "zero" due to a specific type of failure mode, then the results in table 7 are obtained, which compare favorably to those in table 6.

Table 7 – Choquet ERCO with Zero Values for AC2 & AC6

No. of Vehicles-$u(A_i)$	0	1	2	3	4
Sensors and Ratings					
AC1-3 (w=0.2)	0	33.3	23.3	6.7	3.3
AC4-6 (w=0.5)	0	13.3	36.7	16.7	0
IR1-4 (w=0.8)	0	0	10	27.5	67.5
Results					
Choquet Value	0	12.2	24.9	25	54.2
Weight Ave of $u(A_i)$	0	15.5	23.3	16.9	23.6
Omega	0	-3.3	1.54	8.01	30.6

In these examples, the sensor confidences for AC1-3 and AC4-6 could result in highly unreliable responses. AC1-3 provides very unreliable data (0.2), and AC4-6 responses are only as good as a coin flip (0.5), which is why their results were zeroed by the Shapley-Grofman conditioning. Better acoustic sensors might provide more meaningful results. If the inputs from the IR sensors are weighted less (0.6), and a weight of 0.8 for AC1-3 is established, the following results in table 8 are obtained.

Table 8 – Sensor Allocations after Shapley-Grofman Weighting for Increased Confidence Values (0.8, 0.5, 0.6)

No. of Vehicles	0	1	2	3	4
Sensors and Ratings					
AC1 (0.8)	0	1.39	0	0	0
AC2 (0.8)	0	1.39	0	0	0
AC3 (0.8)	0	1.39	0	0	0
AC4 (0.5)	0	0	0	0	0
AC5 (0.5)	0	0	0	0	0
AC6 (0.5)	0	0	0	0	0
IR1 (0.6)	0	0	0	0	0.41
IR2 (0.6)	0	0	0	0	0.41
IR3 (0.6)	0	0	0	0	0.41
IR4 (0.6)	0	0	0	0	0.41
Vote Totals	0	4.17	0	0	1.64

The equivalent Choquet values are shown in table 9.

Table 9 – Choquet Convoy Assessments for Increased Confidence Values (0.8, 0.5, 0.6)

No. of Vehicles-$u(A_i)$ / Sensors and Ratings	0	1	2	3	4
AC1-3 (w=0.8)	0	66.7	23.3	6.7	3.3
AC4-6 (w=0.5)	0	16.7	63.3	20	0
IR1-4 (w=0.6)	0	0	10	27.5	67.5
Results					
Choquet Value	0	55.4	42.3	22.1	41.7
Weight Ave of $u(A_i)$	0	27.8	32.2	18.1	23.6
Omega	0	27.6	10.1	3.99	18.1

In table 9, one vehicle is the best choice as was also shown in table 8. However, there is strength in the case for two and four vehicles too, although the Omega values more clearly point to one vehicle.

Finally, if the weight for both the IR sensors and AC1-3 is set to 0.8, then by inspection the voting response would be 4.17 for one vehicle and 5.56 for four. This would reflect a conflict for a decision-maker and is skewed more towards four vehicles due to the additional IR sensor. The Choquet responses are shown in table 10.

Table 10 – Choquet Convoy Assessments for Increased Confidence Values (0.8, 0.5, 0.8)

No. of Vehicles-$\mu(A_i)$ / Sensors and Ratings	0	1	2	3	4
AC1-3 (w=0.8)	0	66.7	23.3	6.7	3.3
AC4-6 (w=0.5)	0	16.7	63.3	20	0
IR1-4 (w=0.8)	0	0	10	27.5	67.5
Results					
Choquet Value	0	55.3	42.1	24.8	54.6
Weight Ave of $\mu(A_i)$	0	27.8	32.2	18.1	23.6
Omega	0	27.5	9.9	6.73	31

For the results in table 10, the Choquet value for four vehicles is slightly less than that for one vehicle, but the Omega value is shifted towards the four vehicle solution, showing a conflict exists in this example case.

Conclusions

This paper explored the ERDF properties of voting and the Choquet integral fusion methods. In both cases, it appears that they would satisfy the requirements for the CAS SoS described in this paper. Some thoughts on the results are captured in the following paragraphs.

Some sort of averaging of the results from the same sensor types with the same confidence values may be the best approach with the Shapley-Grofman voting method so that apparent redundancies in individual reporting from sensor types (AC1-3 vs. AC4-6 vs. IR1-4) don't skew the overall results. What constitutes redundant information is important to know for anyone building an ERCO SoS.

The Choquet approach maintains values for uncertain evidence such as for the two and three vehicle case that are zeroed out via voting fusion – only true zero evidence is assigned a zero such as for the zero vehicle case. This may be important in some applications where fusion is done over relatively long periods of time, such as the classification of undersea tracks or land vehicles. As such, the Choquet approach may be better at detecting more subtle data changes and their relationships, such as distinguishing between no input and missing inputs and small changes in sensor confidence values as well as revealing changes in direction of assessments.

However, the Choquet approach is restricted for closed-order solutions of no more than four simultaneous inputs (but interpolation can be used with high accuracy for larger numbers of inputs). It is also more complex and algorithmically demanding, although the λ values can be pre-computed for a known set of weights. The Choquet approach may be best suited for higher-order fusion demands such as knowledge generation (Warren 1999), especially with an automated decision threshold capability based on risk tolerance (Schuck and Blasch 2010).

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