STRATEGIC INFORMATION SYNTHESIS BY GLOBULAR KNOWLEDGE FUSION

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ABSTRACT

A method is proposed to combine high level numerical information for the purpose of strategic decision making. The term Globular Knowledge Fusion is applied to describe a non-additive aggregation process which enables structures of knowledge variables to be developed that embed tradeoff information in the multi-tier global values. At the highest level of integration, Globular Knowledge Fusion enables a single meta-system metric to be computed that reflects the big-picture.

1. INTRODUCTION

Strategic decisions are frequently based on the combination of several types of high level information. Such information may be soft or incomplete to varying degrees, as well as being loosely coupled in indeterminate ways. This paper introduces the construct of Globular Knowledge Fusion (GKF) to address a general difficulty pertaining to information synthesis in such complex decision problems where information interdependencies can be present. In this context, "fusion" is used to describe the fundamental information aggregation process whereby a *single* meta-value is derived from various input information. Recently, the term "knowledge fusion" has also been used in another context [4] to refer to a representational problem existing when heterogeneous information is shared and processed across distributed systems. However, GKF does not address this type of representational problem but rather applies to the mathematical integration of interdependent quantitative values that are measures of diverse aspects of a complex situation. In effect, GKF is a transform which integrates the separate aspects into the super-system plane. After first outlining the different characteristics of Data, Information and Knowledge fusion, the method of applying a non-linear functional called the Choquet Integral is described to achieve an overview or global understanding of a complex situation.

2. INFORMATION SYNTHESIS

Three fundamentally distinct types of information synthesis can be identified based on the nature of the input information and the functional characteristics and objectives of the process. These distinct categories of information synthesis will be described here as Data, Information and Knowledge fusion. But before they can be distinguished, fusion itself will be differentiated from aggregation.

Aggregation and Fusion.
A wide variety of aggregation operators exist for summing numerical information: non-linear and linear, compensatory and non-compensatory[13]. With compensatory operators, higher values can cancel the effect of lower values on the aggregate value and non-compensatory operators aim to mitigate this effect to some degree. In contrast to aggregation operations, a fusion process generally *extracts* some item of information (or knowledge) from a variety of input information for which independency is not a necessary condition. As such, it *processes* input information rather than aggregating values. Fusion also has many variants and the US Department of Defense has identified four different levels for threat evaluation applications. GKF actually stands at the junction of aggregation and fusion because interdependent knowledge metrics are summed, or integrated, using non-additive measures to extract a form of meta-information. Thus it does not simply sum information by means of an additive compensatory operator as is appropriate with independent information, but rather interactively amalgamates the information.

Data Fusion
In general, data fusion uses a variety of computational mechanisms (such as parsing, filtering, clustering) to extract information from rich streams of data usually obtained from sensors.

Information Fusion
Information fusion can be distinguished from data fusion by the use of knowledge-bases of various forms such as rule sets, case sets, or behavioural patterns. Such applications in the areas of mechatronics, threat analysis and target identification, may use rich or sparse data to extract the output knowledge. In general, the variables are in the form of classified objects with distinguished features, rather than simple quantitative variables.

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Knowledge Fusion

Knowledge Fusion is characterised by a small amount of input information, down to only a few elements. In this case, the input knowledge elements are of a higher level of strategic value and may have been generated by information fusion or other complex forms of pre-processing. On the other hand, the input may simply be subjective estimates from domain experts based on experience. The descriptor "knowledge" has been applied to distinguish this kind of input from data (and metadata) and some examples of such abstacted variables are Lifecycle Cost, Situation Risk, and Military Force Readiness. Such input function values may be crisp or fuzzy real numbers or even linguistic ratings. The importance weights associated with these variables (credibilities or reliabilities) may be unequal but must be crisp in the proposed method so need defuzzification if initially acquired as fuzzy estimates. If the function values are fuzzy then the aggregate will be fuzzy.

GKF addresses the problem of how to synthesise such information when interdependencies exist between the abstracted variables, either explicitly or implicitly. Explicit interdependencies may arise from inter-element causal influences, or partial sharing of information as could be evidenced in threat estimates derived from separate *coalition force members*. Implicit interdependencies may be present as a form of synergy introduced by the human cognitive process that interprets numerical information and which has been shown by cognitive researchers to be sensitive to patterns in information. In both cases, the interdependencies are indeterminate and unquantifiable, but nevertheless, do require to be acknowledged if the process of information synthesis is to be meaningful. This kind of indeterminate interdependency network differs from other network models where a substantial amount of training data may be available from which the link strengths can be learned. With strategic decision making, there is more likely a very limited amount of information that can be temporally related. In other words, insufficient information is available for training a network model.

GKF is also a general process whereby knowledge synthesis can occur through successive levels, or tiers, of a decision model forming what can be called globular knowledge structures. The term "globular" has been chosen rather than the term "molecular" to highlight the similarity with geometric measure theory and complex bubble shapes, which the author suggests helps to visualise this kind of interpenetrating bubble-like fusion process. "Molecular" on the other hand, describes the growth of a structure by additive aggregation through the joining of extra atoms to their attraction points, which corresponds more to a hierarchical decision structure. In other words, "globular" is intended to refer to non-linear and non-additive aggregation where the successive surface structures of interpenetrating component bubbles represent the values of the decision variable. Figure 1 illustrates a general multi-tier structure of knowledge variables where information can be shared and used across levels which differentiates them from hierarchical models. Such abstracted variables are defined from a top-down perspective and are mostly qualitative and value-based, their measures being derived by the GKF mechanism that is metaphorically shown in Figure 2. Thus, the form of strategic problem that GKF addresses is synthesising a relatively small number of high level variables between which loose couplings exist of some sort. Typical applications are performance evaluation of complex systems or *interdependent* Cost, Benefit and Risk evaluation of decision alternatives. Moreover, the "satisficing" concept for situations where no ideal or best solution obviously exists between combinations of variables due to tradeoffs, describes this general decision making problem. And although this paper does emphasise high level applications, low level and more tangible forms of the problem can also be found as with cut-plan selection in sheet-metal fabrication and wooden pallet manufacture. Three examples of such meta-variable synthesis are shown in Figure 3: a Plant Operations Performance Measure, the Decision Value (or Merit) for a decision alternative, and an integrated Financial Performance Measure for a company based on long and short term considerations.

3. THE CHOQUET INTEGRAL FOR GLOBULAR KNOWLEDGE FUSION

The limitations of simple weighted aggregation (WAV) in decision analysis, where high utility values can compensate for low values, has been previously identified by Zeleny [11]. To address one manifestation of this problem, Zeleny [10] has introduced the concept of "cognitive equilibrium" for the purpose of modelling a fundamental feature of the human cognitive process which synthesises information according to the degree of consistency or balance between information elements. Zeleny [12] has also proposed an alternative method to weighted utility aggregation for information aggregation, using distance measures from ideal values of the information elements. While that method does model contextual variations that can affect aggregation, it still adopts additive procedures and so is not adequate for systemic information with interdependencies. To aggregate information in a manner that *jointly* reflects individual element weights and elemental subset anomalies due to interdependencies or inter-element disparities, this paper proposes another method [7][8] using a non-additive fuzzy integral called the Choquet integral [1][2][3]. The Choquet integral is fundamentally different to the large variety of non-linear aggregation operators existing in the literature that perform operations on *individual* elements, often for the purpose of approximating an optimistic or pessimistic human decision maker. The main difference is that fuzzy measure *subsets* of information are aggregated rather than functions of individual elements and this feature enables inter-element interdependencies and non-linearities to be captured.

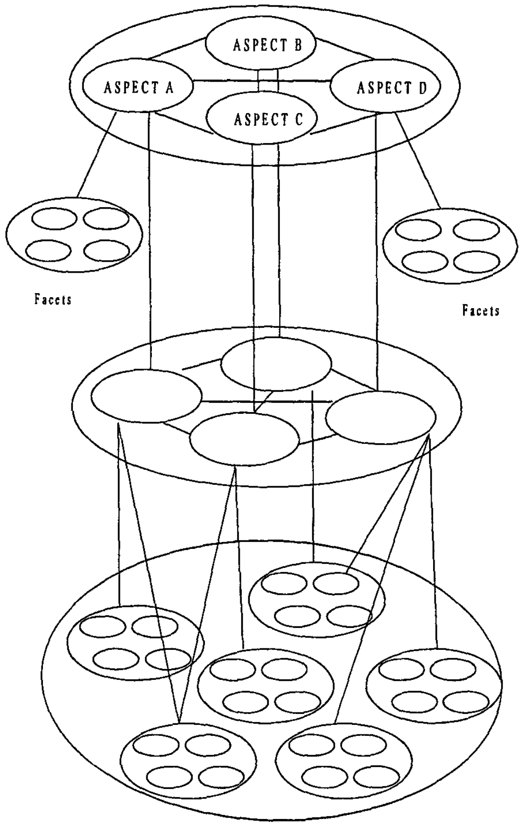

Figure 1: A Multi-Tier Knowledge Structure

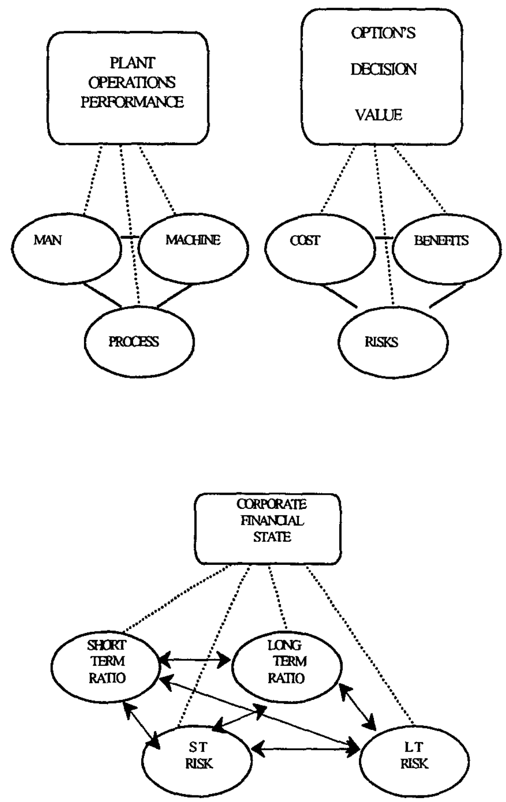

Figure 3: Strategic Meta-Variable Examples

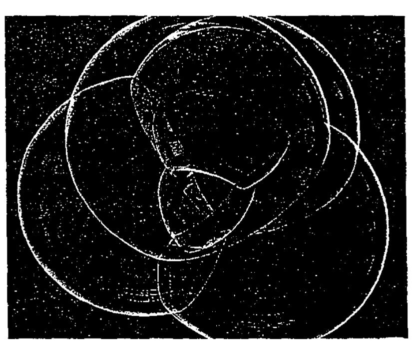

Figure 2: The Globular Fusion Metaphor

The Choquet Integral has been shown to be an extension of the Lebesgue integral [6] and reduces to the Lebesgue integral for additive measures. It is monotonic, idempotent, associative, but not in general commutative. Grabisch [2] has shown that any commutative Choquet integral reduces to an Ordered Weighted Average [9]. There are two basic forms as described in [3] and the method of implementation for GKF is as follows.

The less common formulation of the Choquet integral (C) is used in its discrete form, which clearly depicts non-linear weighted aggregation of function values by aggregating the product of the marginal increase of subset weights and the function values :

$$C(\cdot) = \sum_{i=1}^{n} (\mu(A_i) - \mu(A_{i-1})) f(x_i) \text{ ....(1)}$$

where f(x) is the function value, $\mu(A)$ is the importance of factor subset A which is the set of factors where $f(x) \geq f(x_i)$, and $\mu(A_1) \leq \mu(A_2) \leq \ldots \leq 1$, with $\mu(A_n) = 1$.

Fusion of function values is then achieved through the following steps.

1. For a fixed set of factor importance values (w), determine a non-additivity constant λ: $[-1,+\infty]$ for the Sugeno g_λ fuzzy measure[5] from the equation,

$$\lambda + 1 = \prod_{i=1}^{n} (1 + w_i \lambda) \text{ ....(2)}$$

   This assumes that the *n* factors completely define the aggregate variable. Sugeno [5] has shown that a unique root always exists which is non-zero and ≥ -1. The λ value so determined is constant for each group of factors and only changes when the factor importance ratings (w) are changed.
2. Order the function values by decreasing size.
3. For the ordered factors calculate the subset weight $\mu(A_i)$ for increasing subsets of factors starting with the highest value, as determined by the Sugeno g_λ fuzzy measure,

$$\mu(A_i) = \mu(A_{i-1}) + w_i + \lambda\, w_i\, \mu(A_{i-1}) \text{.......(3)}$$

   where w_i = weight factor i, and $\mu(A_0) = 0$
4. Use equation (1) above to form a global Choquet value for the group of values.

Synergy and Superadditivity

In equation (3) a positive λ implements superadditivity in increasing subset weights(measures). This effect can be used to capture synergy between the individual function values whereby values close together have an increasing influence on the aggregate value, but divergent or disparate values have a decreasing effect on the aggregate value. Tables 1, 2 and 4 demonstrate superadditive aggregation and the sets of more disparate data within Table 4 illustrate Choquet aggregate values further below the WAV (the aggregate always being below with superadditivity). This effect is especially relevant to "satisficing" problems and the Cognitive Equilibrium concept because the degree of inconsistency within sets of values (representing tradeoffs) is directly reflected in the lower aggregate value.

Such a reward form of synergy based on consistency can also be combined with a magnification function for values beyond certain thresholds. This additional reinforcement may be appropriate when combining expert opinions, for example, where mutual agreement on the high (or low) likelihood of an event could justify likelihood reinforcement. Generally, however, this would only be suitable at extremal values and is demonstrated by the following non-linear function.

Synergy Aggregate = $WAV\,(1.1 - \Omega/80) - \Omega^2/15$.

where $\Omega = WAV - C(\cdot)$.

Example likelihood aggregates computed when WAV > 0.8 say, and for a WAV = 88 (0.88) and various Ω (information inconsistencies) are:

$\Omega = 0 \rightarrow 96.8$, $\Omega = 2 \rightarrow 94.3$, $\Omega = 4 \rightarrow 91.3$,
$\Omega = 6 \rightarrow 87.8$, $\Omega = 8 \rightarrow 83.7$, $\Omega = 10 \rightarrow 79.1$.

Thus, superadditivity with the Choquet integral generally results in an aggregate below the WAV and towards the Minimum by an amount Ω determined by the degree of consistency of the information or function values. However, this consistency dependent aggregation may be modified and pushed beyond the Maximum or Minimum by using an aggregation expression that is a function of Ω as in the example above. Using such expressions, the aggregation process can then have designed non-linearities that depend upon the degree of consistency of the data.

Resource	Global Value (U_i)	Weight (w)	$\mu(A_i)$	$\mu(A_i)$-$\mu(A_{i-1})$ (Δ)	$U_i\,\Delta$
Workforce	63	0.07	0.0700	0.0700	4.410
Process	42	0.07	0.2925	0.2225	9.345
Equipment	21	0.07	1.0000	0.7075	14.858
	Median = 42	Sum = 0.21 λ = 31.130	SAV=WAV = 42		C(PL) =28.6

Table 1: Plant Measure- Equal Superadditive Weights of 0.07

Resource	Global Value (U_i)	Weight (w)	$\mu(A_i)$	$\mu(A_i)$-$\mu(A_{i-1})$ (Δ)	$U_i\,\Delta$
Workforce	63	0.15	0.150	0.150	9.45
Process	42	0.15	0.440	0.290	12.18
Equipment	21	0.15	1.0000	0.560	11.76
	Median = 42	Sum = 0.45 λ = 6.2161	SAV=WAV = 42 Ω = -8.6		C(PL) =33.4

Table 2: Plant Measure- Equal Superadditive Weights of 0.15

FACTOR #	Name	Updated Value (U_i)	Individual Importance (w_i)	$\mu(A_i)$	$\mu(A_i)-\mu(A_{i-1})$ (Δ)	$U_i\Delta$	$\Sigma U_i\Delta$
1	# Accidents Minor	0.75	0.25	0.2500	0.2500	0.1875	0.1875
2	Tardiness	0.66	0.175	0.3866	0.1366	0.0902	0.2777
3	Turnover	0.57	0.10	0.4527	0.0661	0.0377	0.3154
4	Participation	0.48	0.325	0.6487	0.1960	0.0941	0.4095
5	SOP Deviation	0.42	0.25	0.7566	0.1079	0.0453	0.4548
6	Cheer	0.39	0.325	0.8660	0.1094	0.0427	0.4975
7	# Accidents Major	0.32	0.45	0.9744	0.1084	0.0347	0.5322
8	House Keeping	0.25	0.175	1.0000	0.0256	0.0064	C(W)= 0.5386
λ = -0.8765 Median U_i = 0.45			Sum w = 2.05	SAV = 0.470 WAV = 0.456		C(W) - WAV = + 0.08	

Table 3: A Global Workforce Measure by Subadditive Weights

Set Number	Resource Global Measures Upper	Middle	Lower	Range	Weighted Average	Choquet C(PL)	C(PL) Gap Ω
1	G 92	G 89	G 86	6	89.0	87.8	- 1.2
2	G 96	G 89	G 75	21	86.7	82.2	- 4.5
3	G 92	G 89	M 55	37	78.7	70.4	- 8.3
4	G 92	G 89	B 35	57	72.0	59.2	- 12.8
5	G 92	M 55	M 49	43	65.3	57.2	- 8.1
6	G 92	M 55	B 28	64	58.3	45.5	-12.8
7	G 92	B 35	B 28	64	51.7	39.7	-12.0
8	M 60	M 55	M 49	11	54.7	52.4	-2.3
9	M 60	M 55	B 28	32	47.7	40.7	-7.0
10	M 60	B 35	B 28	32	41.0	34.9	-6.1
11	B 35	B 28	B 23	12	28.7	26.3	-2.4
12	B 37	B 23	B 18	19	26.3	22.4	-3.9

Table 4 : Choquet Integral Senstitivity to Plant Resource Performance Disparities (Equal Superadditive Weights of 0.15)

Redundancy and Subadditivity

Similarly, a negative λ in equation (3) can model redundancy by decreasing the marginal strengths of increasing subset weights. Thus, lower ordered function values are discounted in the weighted subset aggregate resulting in an aggregate value *above* the WAV. Table 3 demonstrates subadditive aggregation of eight facets of Workforce behaviour at an industrial site with a Choquet meta-value *above* the weighted average (17% higher). In order to apply subadditive weights, in general, there would need to be some justification for discounting the lower values and this could be some form of information redundancy, for example. Since no such reason exists for the purpose of evaluating Workforce group performance, superadditive weights would actually be more appropriate in this example instead of the subadditive weights demonstrated in Table 3.

Sensitivity Adjustment

The sensitivity of both superadditive or subadditive aggregation can be simply controlled by scaling the individual factor weights to yield an appropriate size of λ from equation (2). Since all factor weights are scaled by the same constant, their ordinal relationships are not disturbed by such scaling. This method of implementing the Choquet integral differs from many others in the literature since it does not focus on how to determine the power set of fuzzy weights (measures). And because the function values have been treated as a *system*, the power set of fuzzy measures is determined only by the *order* of function values. In this way, there is no unique or right set of fuzzy measures which avoids the problem of determining a large number of coalition subset weights. However, by using the Sugeno g_λ measure to determine subset weights, subadditivity and superadditivity cannot be mixed as it can with Choquet integral aggregation in non-systemic multicriteria decision models with independent factors or attributes. But for the synthesis of systemic information with explicit or implicit relationships, mixing these two forms of non-additivity is not desirable since it would not coherently capture consistency or redundancy. Table 4 demonstrates superadditive Choquet fusion for all combinations of three plant resource performance measures: Good (G), Medium (M), and Bad (B). Using equal superadditive weights of 0.15, the less consistent sets yield Choquet meta-values further below the weighted averages (the C(PL) Gap Ω), an effect which could be increased further by lowering the equal weights below 0.15.

4. CONCLUSIONS

A process called Globular Knowledge Fusion using the Choquet integral has been proposed for combining strategic information which is loosely coupled. The method is not computationally demanding and also avoids the difficulty of determining the power set of subset weights which often complicates the application of the Choquet integral for non-additive information aggregation. Furthermore, the aggregation sensitivity to function value disparities can be simply adjusted to the required level. The method can also cater for a variety of interdependencies since it enables either synergy or redundancy effects to be modelled by scaling the importance weights to superadditive or subadditive values accordingly. By using the GKF process, a structure or architecture of knowledge variables describing aspects of complex situations can be synthesised into multi-level global aggregates, which directly embed tradeoff information on disparities between the diverse facets of the problem. Such global knowledge variables derived by GKF can then be used to evaluate what is happening overall and provide a coherent overview or insight into the big-picture.

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