Application of Evidence Theory and Discounting Techniques to Aerospace Design

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Abstract. Critical decisions are made by decision-makers throughout the life-cycle of large-scale projects. These decisions are crucial as they have a direct impact upon the outcome and the success of projects. To aid decision-makers in the decision making process we present an evidential reasoning framework. This approach utilizes the Dezert-Smarandache theory to fuse heterogeneous evidence sources that suffer from levels of uncertainty, imprecision and conflicts to provide beliefs for decision options. To analyze the impact of source reliability and priority upon the decision making process, a reliability discounting technique and a priority discounting technique, are applied. A maximal consistent subset is constructed to aid in defining where discounting should be applied. Application of the evidential reasoning framework is illustrated using a case study based in the Aerospace domain.

Keywords: evidential reasoning, information fusion, Dezert-Smarandache theory, Dempster-Shafer theory, discounting techniques

1 Introduction

Decision making in large-scale projects are often sophisticated and complex processes where selections have an impact on diverse stages of the project life-cycle and ultimately the outcome of the project. Evidence supporting/opposing the various design options can be extracted from diverse heterogeneous information sources. However, evidence items vary in terms of reliability, completeness, precision and may contain conflicting information. Aerospace is a highly competitive field with constant demands on aircraft production to improve safety, performance, speed, reliability and cost effectiveness [10]. Design decisions made throughout an aircraft life-cycle are critical as they directly effect the factors above. Decision making in Aerospace involves the evaluation of multiple decision options against criteria such as detailed requirement specifications and International Aviation Standards. To address these limitations we propose an evidential reasoning framework to support decision analysis using information fusion techniques based on Belief Function theory to manage uncertainty and conflict in evidence sources. The novelty of this paper lies in the application of these techniques to decision-making in the Aerospace domain.

This research is an element of a larger collaborative project, DEEPFLOW, which encompasses the areas of natural language processing, high performance computing, computational semantics, and reasoning with uncertainty. The project aims to develop a framework to identify, extract and reason with information contained within large complex interrelated documents which can be applied to many diverse problem domains. Information extracted from these data are used as input to the evidential reasoning framework.

Investigations have been performed in the Aerospace domain where various approaches have been applied to reason with data which are incomplete and uncertain. Such approaches include Bayesian theory, Dempster-Shafer theory (DS) and Dezert-Smarandache theory (DSm) which have been used to fuse uncertain and unreliable information in areas involving sensor information fusion [1] and target identification [4] where systems are required to deal with imprecise information and conflicts which may arise among sensors. A study by Xiaoqing *et al.* [5] provides an example of how argumentation and reasoning can be applied to handle uncertainty and conflicts in decision making.

As summarized above, Bayesian methods and Evidence theories such as DS [6] have commonly been used to handle uncertainty. As a generalized probability approach, DS has some distinct features compared with Bayesian theory. DS can represent ignorance caused by lack of information and can aggregate beliefs when new evidence is accumulated. DSm can be considered as a generalization of DS whereby the rule of combination takes into account both uncertain and paradoxical information [3]. In this paper we apply DSm to fuse pieces of evidence for decision making purposes.

Evidence sources involved in the fusion process may not always have equal reliability or priority. Reliability can be viewed as an objective property of an evidence source whereas priority is viewed as a subjective property expressed by an expert [7]. Counter-intuitive results could be obtained if unequal sources are fused and these factors are not taken into consideration. To highlight the importance of all this in the decision making process we apply two discounting techniques: reliability discounting using Shafer's classical discounting approach and priority discounting based on the importance discounting technique [7]. We construct a maximal consistent subset to aid in defining where discounting should be applied. To evaluate the proposed framework we present a scenario detailing a decision making process in which a design engineer selects a material to construct a wing spar of an aircraft. A spar is an integral structural member of the wing which carries the flight loads and the weight of the wings.

The paper is organized as follows: in section 2 the basics of Evidence theory and combination rules are introduced. In section 3 the reliability discounting and priority discounting techniques are detailed. A case study in section 4 presents an applied scenario based in the Aerospace domain comparing DS and DSm approaches and the impact of discounting factors on decision analysis. Conclusions are provided in section 5.

2 Theory of Belief Functions

DS Theory DS (evidential theory) is a generalization of traditional probability. This theory provides a mathematical formalism to model our belief and uncertainty on possible decision options for a given decision making process. In DS the frame of discernment denoted by $\Theta = \{\theta_1, ..., \theta_n\}$ contains a finite set of n exclusive and exhaustive hypotheses. The set of subsets of Θ is denoted by the power set 2^{Θ}. For instance, $\{A, C, W\}$ is the frame for materials (aluminium, composite, wood) from which an engineer selects one to construct a wing spar.
DSm DSm proposes new models for the frame of discernment and new rules of combination that take into account both paradoxical and uncertain information. In DSm, the free DSm model, $\Theta = \{\theta_1, ..., \theta_n\}$ is assumed to be exhaustive but not necessarily exclusive due to the intrinsic nature of its elements, the set of subsets are denoted by the hyper power-set D^{Θ} (Dedekind's lattice) described in detail in [8] which is created with $\cup$ and $\cap$ operators. Using the hybrid DSm (hDSm) model integrity constraints can be set on elements of Θ reducing cardinality and computation time compared to the free model. When Shafer's model holds i.e. all exclusivity constraints on elements are included the D^{Θ} reduces to the power set 2^{Θ}. We denote G^{Θ} the general set on which will be defined the basic belief assignments, i.e. $G^{\Theta} = 2^{\Theta}$ when DS is adopted or $G^{\Theta} = D^{\Theta}$ when DSm is preferred depending on the nature of the problem.

A basic belief assignment (bba) expressing belief assigned to the elements of G^{Θ} provided by an evidential source is a mapping function $m : G^{\Theta} \to [0, 1]$ representing the distribution of belief satisfying the conditions:

$$m(\emptyset) = 0 \;\text{ and }\; \sum_{A \in G^{\Theta}} m(A) = 1 \tag{1}$$

In evidence theory, a probability range is used to represent uncertainty. The lower bounds of this probability is called ***Belief(Bel)*** and the upper bounds ***Plausibility(Pl)***. The generalized Bl and the Pl for any proposition $A \in G^{\Theta}$ can be obtained by:

$$Bel(A) = \sum_{\substack{B \subseteq A \\ B \in G^{\Theta}}} m(B) \;\text{ and }\; Pl(A) = \sum_{\substack{B \cap A \neq 0 \\ B \in G^{\Theta}}} m(B) \tag{2}$$

In DSm the Proportional Conflict Redistribution Rule no. 5 (PCR5) has been proposed as an alternative to Dempster's rule for combining highly conflicting sources of evidence. Below Dempster's combination rule and PCR5 are briefly detailed, a complete presentation of DSm can be found in [8].

Dempster's Rule of Combination In DS, Dempster's rule of combination is symbolized by the operator $\oplus$ and used to fuse two distinct sources of evidence B_1 and B_2 over the same frame Θ. Let Bel_1 and Bel_2 represent two belief functions over the same frame Θ and m_1 and m_2 their respective bbas. The combined belief function $Bel = Bel_1 \oplus Bel_2$ is obtained by the combination of m_1 and m_2 as: $m(\emptyset) = 0$ and $\forall C \neq \emptyset \subseteq \Theta$

$$m(C) \equiv [m_1 \oplus m_2](C) = \frac{\sum_{A \cap B = C} m_1(A) m_2(B)}{1 - \sum_{A \cap B = \emptyset} m_1(A) m_2(B)} \tag{3}$$

Dempster's rule of combination is associative ($[m_1 \oplus m_2] \oplus m_3 = m_1 \oplus [m_2 \oplus m_3]$) and commutative ($m_1 \oplus m_2 = m_2 \oplus m_1$).

PCR5 Rule of Combination The PCR5 rule can be used in DSm to combine bbas. PCR5 transfers the conflicting mass only to those elements that are involved in the conflict and proportionally to their individual masses. This preserves the specificity of the information in the fusion process [3]. For two independent bbas m_1 and m_2 the PCR5 rule defined by [8] is as follows: $m_{PCR5}(\emptyset) = 0$ and $\forall (X \neq \emptyset) \in G^{\Theta}$

$$m_{PCR5}(A) = \sum_{\substack{X_1, X_2 \in G^{\Theta} \\ X_1 \cap X_2 = A}} m_1(X_1) m_2(X_2) + \sum_{\substack{X \in G^{\Theta} \\ X \cap A = \emptyset}} \left[\frac{m_1(A)^2 m_2(X)}{m_1(A) + m_2(X)} + \frac{m_2(A)^2 m_1(X)}{m_2(A) + m_1(X)}\right] \tag{4}$$

All fractions in (4) which have a denominator of zero are discarded. All propositions/sets in the formula are in canonical form. PCR5 is commutative and not associative but quasi-associative.

Probabilistic Transformation We need to obtain pignistic probabilities for decision making purposes for this study. Fused beliefs are mapped to a probability measure using the generalized pignistic transformation approach *DSmP* [2], an alternative to the familiar approach *BetP* proposed by Smets *et al* [9]. *DSmP* is advantageous as it can be applied to all models (DS, DSm, hDSm) and can work on both refined and non-refined frames. *DSmP* is defined by $DSmP_{\epsilon}(\emptyset) = 0$ and $\forall X \in G^{\Theta}$ by

$$DSmP_{\epsilon}(X) = \sum_{Y \in G^{\Theta}} \frac{\sum_{\substack{Z \subseteq X \cap Y \\ C(Z)=1}} m(Z) + \epsilon \cdot C(X \cap Y)}{\sum_{\substack{Z \subseteq Y \\ C(Z)=1}} m(Z) + \epsilon \cdot C(X \cap Y)} m(Y) \tag{5}$$

where G^{Θ} corresponds to the hyper power set; $C(X \cap Y)$ and $C(Y)$ denote the cardinals of the sets $X \cap Y$ and Y respectively; $\epsilon \geq 0$ is a tuning parameter which allows the value to reach the maximum Probabilistic Information Content (PIC) of the approximation of m into a subjective probability measure [2]. The PIC value is applied to measure distribution quality for decision-making. The PIC of a probability measure denoted P associated with a probabilistic source over a discrete finite set $\Theta = \{\theta_1, ..., \theta_n\}$ is defined by:

$$PIC(P) = 1 + \frac{1}{H_{max}} \cdot \sum_{i=1}^{n} P\{\theta_i\} log_2(P\{\theta_i\}) \tag{6}$$

where H_{max} is the maximum entropy value. A PIC value of 1 indicates the total knowledge to make a correct decision is available whereas zero indicates the knowledge to make a correct decision does not exist [2].

3 Evidential Operations

Evidence to support or refute design options in a decision making process can be extracted from numerous information sources including reports, journals and magazine articles. Some sources may be regarded as being reliable or have a higher priority than others. It is important to manage these factors in the fusion process to reduce errors in reporting beliefs for decision options. Prior knowledge is applied to estimate both the reliability and priority discounting values.

To aid with determining which sources should be discounted before fusion, we can construct a *maximal consistent subset*. This involves constructing a subset of sources that are consistent with each other. Discounting could be applied to sources deemed dissimilar or non-coherent. To measure the coherence between evidence sources the Euclidean similarity measure based on distance is applied, other distance measure are also applicable. This measure is commutative. Let $\Theta = \{\theta_1, ..., \theta_n\}$ where $n > 1$ and m_1 and m_2 are defined over G^{Θ}, X_i is the *ith* element of G^{Θ} and $|G^{\Theta}|$ the cardinality of G^{Θ}, the function can be defined by:

$$S(m_1, m_2) = 1\frac{1}{\sqrt{2}}\sqrt{\sum_{i=1}^{|G^{\Theta}|}(m_1(X_i) - m_2(X_i))^2} \tag{7}$$

Application of other similarity approaches could also have been applied, however, Euclidean distance was selected for simplicity.

Reliability Discounting Techniques In reliability discounting a discounting factor α in $[0, 1]$ can be applied to characterize the quality of an evidence source [7]. For instance, evidence extracted from an aviation journal is considered higher quality than a blog post. The reliability factor transforms the belief of each source to reflect credibility. Shafer's discounting technique [6] has been proposed for the combination of unreliable evidence sources. Incorporation of the reliability factor $1 - \alpha \in [0, 1]$ in the decision making process is defined as:

$$\begin{cases} m_\alpha(X) = \alpha \cdot m(X), \forall X \subset \Theta \\ m_\alpha(\Theta) = \alpha \cdot m(\Theta) + (1 - \alpha) \end{cases} \tag{8}$$

whereby $\alpha = 0$ represents a fully reliable source and $\alpha = 1$ an unreliable source. The discounted mass is committed to $m(\Theta)$. Using prior knowledge, we set reliability factors whereby evidence extracted from a journal, magazine and blog post are represented by the factors $\alpha = 0.1$, $\alpha = 0.3$, $\alpha = 0.7$ respectively.

Priority Discounting Technique Source priority can be viewed as a subjective attribute whereby an expert can assign a priority value to an individual source [3]. We characterize priority using a factor denoted β in $[0, 1]$, representative of a priority weight assigned by an expert to a source. The highest priority assigned to a source is characterized by $\beta = 1$ and minimum $\beta = 0$. In this research, pieces of evidence have been ranked in accordance to priority; for instance, it is essential that the material selected to construct a wing spar is verified to be *safe*. Therefore a piece of evidence supporting the material safety is set with a priority factor of 1. Priority discounting is defined with respect to

$\emptyset$ and not Θ as in the Shafer reliability approach. The discounting of a source having a priority factor β can be defined as:

$$\begin{cases} m_\beta(X) = \beta \cdot m(X), \text{ for } X \neq \emptyset \\ m_\beta(\emptyset) = \beta \cdot m(\emptyset) + (1 - \beta) \end{cases} \tag{9}$$

which allows $m(\emptyset) \geq 0$, thereby preserving specificity of the primary information as all focal elements are discounted with same priority factor [7]. When full priority is selected by the expert i.e. $\beta = 1$, the source will retain its full importance in the fusion process. Therefore the original mass of the bba is not changed. PCR5 is applied to demonstrate the fusion process when priority discounting is used as Dempster's rule of combination does not respond to the discounting of sources towards the empty set [7]

4 Case Study

This study is intended to illustrate how heterogeneous information from disparate sources can be fused to aid engineers when deciding upon material for a wing spar. The PCR5 rule of combination has been selected to fuse pieces of evidence. Dempster's rule of combination is used for comparative purposes as this rule may generate errors in decision making when the level of conflict between evidence sources is high. Furthermore, priority discounting cannot be illustrated using the DS approach. Before fusion, a maximal consistent subset (i.e. sets of consistent evidential sources) is determined. Obtaining the maximum consistent subset will aid in identifying sources to be discounted. Either reliability or priority discounting can be applied. The aim of applying these approaches is to improve the correctness of fusion results. Decision making is based on pignistic probabilities where results are presented using both *DSmP* and *BetP* transformation methods for comparative purposes.

Standards, Requirements and Evidence The material selected to construct a wing spar must fulfill specified design requirements. It is assumed that an aviation expert has assigned priory and reliability values. To determine if materials adhere to these requirements we have extracted evidence from a total of 50 heterogeneous sources including: 18 journal articles, 6 technical white papers, 9 books, 7 aviation magazines and 10 blogs (argumentation mining is being applied in DEEPFLOW to automatically extract these information). These sources varied in terms of certainty and consistency, and the resulting knowledge base could contain some conflicting evidence. Using this information, an input evidence vector was constructed by mapping the evidence for the design options to relevant design requirements fulfilled or otherwise. A sample vector is presented in Table 1.

4.1 Implementation of Scenario

An engineer has the task of selecting a material from the set: aluminum (A), composites (C) and wood (W) to construct a wing spar. The frame of discernment $\Theta = \{A, C, W\}$, is used in the fusion. For simplification, we assume that the selected material needs to fulfill just four requirements: safety, damage tolerance, ease of fabrication and availability of supply. We use four different evidence

Table 1. Sample Evidence Vector

	Aluminium	Composite	Wood
Evidence	Tolerant material	Damage resistance	Limited availability
Reliability	Journal (0.1)	Magazine (0.3)	Blog (0.7)
Requirement	Safety	Damage Tolerance	Availability
Priority	High priority (1)	High priority (1)	Low priority (0.2)

sources that assign belief to the hypotheses. The estimated respective bbas: m_1, m_2, m_3 and m_4 are given in Table 2. These are estimated using information from the digital knowledge base along with expert knowledge.

Table 2. Basic Belief Assignments for Evidence Sources

	A	C	W	Θ
m_1	0.4	0.5	0	0.1
m_2	0.7	0	0.3	0
m_3	0.2	0.8	0	0
m_4	0.4	0.4	0.1	0.1

Maximal Consistent Subset It is known that conflict between evidence sources can have a detrimental impact upon the fusion process. To address this, we present a methodology to determine a maximal consistent subset. Before fusion is performed, priority or reliability discounting factors can be applied to those bbas which are considered dissimilar. An outline of this methodology is presented in Algorithm 1. The first step is to rank the evidential sources represented by bbas (m_1, m_2, m_3, m_4) based on their information content. Information content values were obtained using the PIC formula detailed in Equation 6. m_4 was identified as obtaining the highest PIC value and this is the first member of a potential maximal consistent subset. In the next step, m_4 is joined by other bbas considered most similar to m_4. The similarity (S) for the subsets: $\{m_4, m_1\}$, $\{m_4, m_2\}$ and $\{m_4, m_3\}$ was calculated. A threshold parameter (tuned by the system designer) was set at 0.65 which was judged an acceptable threshold similarity value. The highest similarity value of 0.86 was obtained for $\{m_4, m_1\}$. Therefore the maximal consistent subset now consists of m_1 and m_4. We measure the similarity between the bbas in the current maximal consistent subset

Algorithm 1 Calculation of Maximal Consistent Subset

FORALL bbas calculate information content using PIC approach
SELECT bba with highest information content, add to maximal consistent subset. If more than one bba have the same PIC value, choose one arbitrarily
REPEAT
  FIND most similar bbas using distance measure to those bbas in maximal consistent subset
  IF similarity value > threshold then join bba to maximal consistent subset
UNTIL similarity values for all remaining bbas not in maximal consistent subset obtain value < threshold or no bbas remain

and m_2 and m_3, respectively. It was observed that $S(m_2, m_{1,4})$ and $S(m_3, m_{1,4})$ were both low 0.27 and 0.52, respectively (where $m_{1,4}$ represents the both subsets m_1 and m_4). Both these values fall below the threshold parameter, therefore m_2 and m_3 are not considered members of the maximal consistent subset.

To highlight the importance of considering conflict in the decision making process we present a number of examples where evidence sources are fused using PCR5 and Dempster's rule of combination. In the first example evidence sources are considered equal; in the second and third, we use reliability and priority discounting, respectively.

Example 1: No Discounting We present the case where evidence was fused using the PCR5 and Demspter's rule of combination based on the assumption that all sources are equal in terms of reliability and priority. Furthermore, the maximal consistent subset and identification of dissimilar sources were not considered. The results obtained for this scenario are shown in Table 3. Pignistic values are presented for both combination rules, $m_{12}..., m_{1234}$ corresponds to the sequential fusion of the sources $m_1..., m_4$. The PIC criterion was applied to obtain information content values for the probability distributions generated by *DSm* and *BetP*.

Based on the results in Table 3 it can be seen that PCR5 and Dempster's rule of combination assigned different probability values to the hypotheses. Dempster's rule of combination distributes uniformly over all focal elements of 2^{Θ} the total conflicting mass resulting in a potentially imprecise and incorrect result. In comparison, PCR5 obtains more realistic probabilistic values transferring conflicting masses proportionally to non-empty sets.

Table 3. Dempster's Rule of Combination and PCR5 Rule No Discounting

	PCR5						Dempster's Rule of Combination					
	Generalized BetP			$DSmP_{\epsilon=0}$			*BetP*			$DSmP_{\epsilon=0}$		
	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}
A	0.62	0.38	0.40	0.62	0.38	0.40	0.92	1.00	**1.00**	0.92	1.00	**1.00**
C	0.24	0.59	**0.58**	0.24	0.59	**0.58**	0.00	0.00	0.00	0.00	0.00	0.00
W	0.14	0.03	0.02	0.14	0.03	0.02	0.08	0.00	0.00	0.08	0.00	0.00
Θ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PIC			0.30			0.30			1.00			1.00

Example 2: Reliability Discounting Reliability weightings for the pieces of evidence represented by bbas depend on the source from which the information was extracted (where α_1 =journal, α_2 =magazine, α_3 =blog and α_4 =magazine). This results in the discounting factors $\alpha_1 = 0, \alpha_2 = 0.3, \alpha_3 = 0.7, \alpha_4 = 0.3$. Taking into consideration the maximal consistent subset, reliability discounting factors are applied to the dissimilar sources m_2 and m_3. As m_4 is a member of the maximal consistent subset it is not discounted. Table 4 presents results where reliability discounting is applied and evidence sources fused using Dempster's rule of combination and PCR5 respectively. Dempster's rule of combination and PCR5 rule assign the highest belief to hypothesis C followed by A when reliability factors and consistent subsets are considered. By applying reliability

discounting factors the degree of conflict between m_2 and m_3 was reduced. The discounted mass was committed to Θ resulting in Dempster's combination rule assigning similar probabilities to the PCR5 approach. This highlights the effect that conflict can have on the fusion process when compared to the results without discounting in Table 3.

Table 4. Dempster's and PCR5 Rule of Combination Results Reliability Discounting

	PCR5						Dempster's Rule of Combination					
	Generalized BetP			$DSmP_{\epsilon=0}$			*BetP*			$DSmP_{\epsilon=0}$		
	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}
A	0.469	0.341	0.364	0.479	0.341	0.364	0.502	0.502	0.351	0.517	0.351	0.351
C	0.485	0.644	**0.615**	0.497	0.651	**0.616**	0.459	0.459	**0.637**	0.470	0.637	**0.639**
W	0.046	0.015	0.021	0.024	0.008	0.020	0.040	0.040	0.012	0.012	0.012	0.009
Θ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PIC			0.32			0.32			0.36			0.37

Example 3: Priority Discounting Pieces of evidence represented by bbas were ranked in order of priority based on the expert opinion of a design engineer (where β_1 =safety, β_2 =availability of supply, β_3 =ease of fabrication and β_4 =damage resistance). The priority factors for the respective four bbas are: $\beta_1 = 1, \beta_2 = 0.2, \beta_3 = 0.6, \beta_4 = 1$. The impact of this approach is demonstrated using the PCR5 rule of combination. m_1 and m_4 were identified as the highest priority bbas and both are members of the maximal consistent subset. By applying priority discounting to m_2 and m_3 we can view the impact on the decision making process in Table 5 where hypothesis C obtains the highest pignistic value followed by A. Marginal higher PIC values (i.e. the probability of making a precise/correct decision is increased) were obtained compared to the PCR5 fusion in Table 3 where no discounting was performed. These results demonstrate how consistency measuring and discounting techniques may be beneficial within decision support systems. Furthermore, the examples reflect the difficulty in decision making within Aerospace. For example, the metal Aluminium has commonly been applied to construct wing spars with advantageous properties including ease of manufacture and repair. In comparison, the use of composites in aircraft is more recent than aluminum resulting in less knowledge on its safety. However, composites are light weight and cost effective. The use of DEEPFLOW offers benefits here. For instance, in the cases of conflicts or inconclusive decisions, DEEPFLOW could further examine and obtain additional evidence from unstructured documents to strengthen or weaken the arguments.

Table 5. PCR5 Rule of Combination with Priority Discounting

	Generalized BetP			$DSmP_{\epsilon=0}$		
	m_{12}	m_{123}	m_{1234}	m_{12}	m_{123}	m_{1234}
A	0.453	0.351	0.372	0.463	0.352	0.372
C	0.508	0.633	**0.606**	0.523	0.643	**0.607**
W	0.039	0.016	0.022	0.013	0.005	0.021
Θ	0.000	0.000	0.000	0.000	0.000	0.000
PIC			0.31			0.32

5 Conclusion

This paper provides an overview of our proposed evidential reasoning framework which is applied in the DEEPFLOW project. Furthermore, we detail a novel application of this framework to decision analysis in the Aerospace domain. A case study was used to illustrate the importance of selecting a valid combination rule to analyze critical design decisions when information is conflicting and uncertain. Furthermore, it highlighted the importance of taking into account discounting factors obtained from prior knowledge and measuring consistency between evidence sources before making design decisions. In future work we will further investigate the complexity of the algorithm to obtain the maximal consistent subset and the impact this has on the fusion process. As part of this research we will also compare and contrast different distance measures to measure similarity. This evidential framework can be applied to aid decision-making in other problem domains where information may be incomplete and unreliable.
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