Combination Algorithm of Probabilistic Argumentation Systems Based on Evidence Theory

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Abstract—Probabilistic Argumentation Systems is an alternative approach for non-monotonic reasoning under uncertainty. It can judge an unknown question in terms of the degree of support and that of possibility about probabilistic entailment. The resulting degree of support and degree of possibility correspond to belief and plausibility, respectively, in the Dempster-Shafer theory of evidence. But the system would result in absurd conclusion because of losing some valuable information in the course of transformation. To overcome this defect, this paper brings forth combination algorithm of Probabilistic Argumentation Systems to avoid the loss of information by using the validity of the decomposition model with conjunction of multi-atomic sets for probabilistic logic reasoning. An illustrative example shows the validity of the proposed method.

Keywords—Probabilistic Argumentation Systems; Dempster-Shafer Theory; Combination Algorithm

I. INTRODUCTION

Different uncertainty inference theories have been developed so far. The most popular approach is the theory of Bayesian inference [8]. More general approaches are evidence theory (D-S theory) [5][8][13], rough sets [3][10][15], and possibility of theory [9][17]. In 1999, R. Haenni brought forward a new and effective theory of uncertain reasoning, which is Probabilistic Argumentation Systems (PAS)[1][10][13]. This system expresses the uncertainty of knowledge by introducing environmental variables combined with logic, and then it can judge an unknown question in terms of the degree of support and that of possibility about probabilistic entailment. Meanwhile, it can also translate PAS into corresponding Dempster-Shafer believe potentials by introducing environmental variables combined with logic, accordingly, it can be used as an effective computational tool for numerical computations. But the system would result in absurd conclusion because of losing some valuable information in the course of transformation. In order to solve the problem, this paper introduces a new combination algorithm of degree of support about probabilistic entailment which based on evidence theory. By using the validity of the decomposition model with conjunction of multi-atomic sets for probabilistic logic reasoning [5], this paper puts forwards a new combination algorithm which can obviously reduce the complexity of probabilistic logic reasoning as well as avoid losing information. Finally, an illustrative example shows that we can get reasonable result by using the combination algorithm.

II. FOUNDATION

The following three subsections provide short overviews on Dempster-Shafer theory [9], probabilistic argumentation systems and the connection between D-S theory and PAS.

A. D-S Theory

The primitive elements of Dempster-Shafer theory are belief functions belφ relative to some given evidence [5]. Other representations of φ are its mass function mφ or its plausibility function pφ. In this paper, we use the notations [φ]m, [φ]bel, and [φ]pl instead of mφ, belφ and pφ, respectively. In accordance with Shafer [6], we speak of belief potentials φ (or potentials for short) when no particular representation is specified. A belief potential φ is defined on a finite set of variables

D = {x1, x2, ..., xn} called domain of φ. We use ΘD to denote the set of all belief potentials relative to D. Every variable xi ∈ D has a corresponding set Θxi of possible values. The Cartesian product ΘD = Θx1 × ... × Θxn, which is the set of possible configurations of D, is called frame of discernment of φ. If D is not explicitly specified, we use d(φ) to denote the domain of φ.

The mass function [φ]m : 2ΘD → [0,1] assigns to every set X ⊆ ΘD a value in [0,1] such that ΣX∈ΘD[φ(X)]m = 1. Mass functions are also called basic probability assignments (bpa). Often, another condition [φ](∅)m = 0 is imposed. A belief potential φ for which this additional condition holds is called normalized. Otherwise, φ is called unnormalized and cφ = [φ](∅)m is the corresponding conflicting mass.

The sets X ⊆ ΘD for which φ[X]m ≠ 0 are called focal sets. FS(φ) denotes the set of all focal sets of φ. A belief potential is usually represented by the collection {(F1, m1), ..., (Fn, mn)} of all pairs (Fi, mi) with Fi ∈ FS(φ) and mi = φ[Fi]m.

Belief functions [φ]b : 2ΘD → [0,1] and plausibility functions [φ]p : 2ΘD → [0,1] are usually defined in terms of corresponding mass functions by
\[
[\varphi(H)]_b = \sum_{X \subseteq H} [\varphi(X)]_m = \sum_{X \subseteq H} [\varphi(X)]_m,
\]
\[
[\varphi(H)]_p = \sum_{X \subseteq H \cup \emptyset} [\varphi(X)]_m = \sum_{X \subseteq H \cup \emptyset} [\varphi(X)]_m,
\]
respectively. By distributing the corresponding proportion of the conflicting mass \(c\) among the non-empty focal sets \(FS(\varphi)/[\emptyset]\) normalized mass, belief, and plausibility functions can be defined by
\[
[\varphi(X)]_m = \begin{cases} 
0, & X = \phi, \\
\dfrac{[\varphi(X)]_m}{1 - C_p}, & \text{otherwise}, 
\end{cases}
\]
\[
[\varphi(H)]_m = \sum_{X \subseteq H} [\varphi(X)]_m = \sum_{X \subseteq H} [\varphi(X)]_m = \dfrac{[\varphi(H)]_m}{1 - C_p},
\]
\[
[\varphi(H)]_p = \sum_{X \subseteq H \cup \emptyset} [\varphi(X)]_m = \sum_{X \subseteq H \cup \emptyset} [\varphi(X)]_m.
\]
The basic operations for belief potentials are combination and marginalization. It takes two potentials \(\varphi_1 \in \Omega_1\) and \(\varphi_2 \in \Omega_2\) and produces a new potential \(\varphi_1 \otimes \varphi_2\) on domain \(D_1 \cup D_2\). Combination is usually defined on mass functions by
\[
[\varphi_1 \otimes \varphi_2(X)]_m = \sum_{X_1 \in \Omega_1(X), X_2 \in \Omega_2(X)} [\varphi_1(X_1)]_m \cdot [\varphi_2(X_2)]_m
\]
where \(X\) represent the vacuous extensions of the sets \(X_1 \subseteq \Omega_1\) and \(X_2 \subseteq \Omega_2\) to the new domain \(D\). Evidence \(\varphi_1\) and \(\varphi_2\) should be independent.

Marginalization takes a belief potential \(\varphi \in \Theta_D\) and produces a new potential \(\varphi^M\) on \(D' \subseteq D\). It is used to focus the information contained in \(\varphi\) to a smaller domain. It is defined in terms of mass functions by
\[
[\varphi^M(X)]_m = \sum_{Y \subseteq D' \subseteq X \subseteq \Omega} [\varphi(Y)]_m
\]
where \(Y^M\) denotes the projection of the set \(Y \subseteq \Omega\) to the new domain \(D'\).

**B. Probabilistic Argumentation Systems**

Recently, developments of abstract argumentation that take into account the uncertainty of arguments have been presented including [19-22]. These introduce a probability assignment for each argument to represent the degree to which the argument is believed to hold, giving rise to a probabilistic argument graph. Because of the connections to other theories of reasoning with uncertain information, particularly to the classical fields of logical and probabilistic reasoning, probabilistic argumentation systems will be investigated in this paper. For the construction of a probabilistic argumentation system, consider two disjoint proposition sets \(A = \{a_1, \ldots, a_m\}\) and \(P = \{p_1, \ldots, p_m\}\)

The elements of \(A\) are called assumptions. They are used to represent uncertain events, unknown circumstances and risks, or possible outcomes. \(N_A = \{0,1\}^m\) represents the set of all possible configurations relative to \(A\). The elements are called scenarios. Terms containing only assumptions represent possible scenarios or states of the unknown or future world, which is denoted \(\tau\).

\(\Gamma_A\) denotes the set of all such terms. \(L_{\tau \rightarrow p}\) denotes the corresponding propositional language. A propositional sentence \(\xi \in A \cup P\) called knowledge base and is often specified by a conjunctively interpreted set \(\Sigma = \{\xi_1, \ldots, \xi_r\} \subseteq C_{\tau \rightarrow p}\) of clauses, where \(C_{\tau \rightarrow p}\) denotes the set of all proper clauses over \(A \cup P\). We use \(d_1 \subseteq A\) to denote the effective sets of propositions appearing in \(\xi\). A second propositional sentence \(h \in L_{\tau \rightarrow p}\) called hypothesis is given to represent open questions or uncertain statements about some of the propositions in \(A \cup P\). If the assumptions are set according to some scenarios \(s \in N_A\), then \(h\) may be a logical consequence of \(\xi\). In other words, \(h\) is supported by certain arguments \(\tau \in \Gamma_A\) or corresponding scenarios \(s \in N_A\). Let \(\xi_{s \rightarrow h} = \tau(s) \land \xi\) be the knowledge base obtained from \(\xi\), then \(N_A\) can be decomposed into three disjoint sets

\[
I_A(\xi) = \{s \in N_A : \xi_{s \rightarrow h} \models \bot\}
\]
\[
SP_A(h, \xi) = \{s \in N_A : \xi_{s \rightarrow h} \models h, \xi_{s \rightarrow h} \neq \bot\}
\]
\[
RF_A(h, \xi) = \{s \in N_A : \xi_{s \rightarrow h} \neq h, \xi_{s \rightarrow h} \neq \bot\}
\]
of inconsistent, supporting, and refuting scenarios, respectively. (\(\bot\) represents the impossible statement). Furthermore,

\[
QS_A(h, \xi) = \{s \in N_A : \xi_{s \rightarrow h} \models h\}
\]
\[
PS_A(h, \xi) = \{s \in N_A : \xi_{s \rightarrow h} \neq h\}
\]
can be defined quasi-supporting and possibility scenarios of \(h\).

So far, hypothesis is only judged qualitatively. A quantitative judgment of the situation becomes possible if every assumption \(a_i \in A\) is linked to a corresponding prior probability \(\pi_i = p(a_i)\). Let \(\Pi = \{\pi_1, \ldots, \pi_m\}\) denote the set of all prior probabilities. We suppose that the assumptions are mutually independent. This defines a probability distribution \(p(\hat{s} = s)\)

\[
\hat{s} = s \in N_A, \quad \text{let } s = \{x_1, \ldots, x_m\}, \quad x_i = 0,1, \quad \text{then } p(\hat{s} = s) = \prod_{i=1}^{m} \pi_i x_i (1 - \pi_i) \cdot x_i \text{ over}
\]
the set \( N_A \) of scenarios. A quadruple \((\xi, P, A, \Pi)\) is then called probabilistic argumentation system \([1]\).

In order to judge \( h \) quantitatively,
\[
dqs(h, \xi) = p(\hat{s} \in QS_A(h, \xi)).
\]
\[
dsp(h, \xi) = p(\hat{s} \in SP_A(h, \xi) | \hat{s} \notin I_A(\xi))
\]

And
\[
dps(h, \xi) = p(\hat{s} \in RF_A(h, \xi) | \hat{s} \notin I_A(\xi))
\]

are defined degree of quasi-supporting, degree of support and degree of possibility of \( h \) relative to \( \xi \), respectively.

C. The Connection between D-S and PAS

PAS can translate PAS into corresponding Dempster-Shafer believe potentials by constructing mass function, accordingly, it can be used as an effective computational tool for numerical computations.

**Theorem 1** Let \((\xi, P, A, \Pi)\) be a probabilistic argumentation system. If a belief potential \( \varphi \in \Theta_Q \) is defined by \( \varphi[X]_m = \sum_{x \in N_0(\xi, \ldots)} p(\hat{s} = s) \), then
\[
dqs(h, \xi) = [\varphi^\ominus Q(H)]_m, \quad \text{for all } h \in L_{A,P}, \quad H = N_0(h), \quad \text{and } Q = d_{A,P}(h).
\]

**Theorem 2** Let \((\xi, P, A, \Pi)\) be a probabilistic argumentation system. If \( \varphi \in \Theta_Q \) is a belief potential with \( Q \subseteq A \cup P \) and \( dqs(h, \xi) = [\varphi(H)]_m \), then
\[
1) \quad dsp(h, \xi) = [\varphi(H)]_m,
\]
\[
2) \quad dps(h, \xi) = [\varphi(H)]_m,
\]

for all \( h \in L_Q \) and \( H = N_0(h) \).

**Example 1** Suppose that two computers \( x_1, x_2 \) are connected using two wires \( a, b \) of different quality as shown in Figure 1. Our main point of interest is whether or not a mail which is sent from the first computer on the left reaches the second computer on the right. We suppose that \( p(a) = 0.8, \ p(b) = 0.5 \).

\[
\begin{array}{c}
\xrightarrow{a} \\
\xrightarrow{b}
\end{array}
\]

Fig. 1 Two computers are connected

To answer this question, we construct a PAS, where the set of assumptions \( A = \{a, b\} \), the set of propositions \( P = \{x_1, x_2\} \), the knowledge base \( \xi \) consists of 2 rules of the form \( x_1 \land a \rightarrow x_2, \ x_1 \land b \rightarrow x_2 \). We can transform the form into an equivalent set of clause \( \Sigma = \{-x_1 \lor -a \lor x_2, -x_1 \lor -b \lor x_2\} \). It may now be interesting to compute the degree of support that a mail which is sent from the first computer on the left reaches the second computer on the right. This corresponds to computing \( dsp(x_1 \rightarrow x_2, \xi) \). Obviously, there are four scenarios \( s_1 = (1,1), s_2 = (0,1), s_3 = (1,0), s_4 = (0,0) \). As a consequence, we have
\[
\begin{align*}
\xi_{s_1} &= a \land b \land (-x_1 \lor x_2) \\
p(\hat{s} = s_1) &= 0.8 \times 0.5 = 0.4 \\
\xi_{s_2} &= -a \land b \land (-x_1 \lor x_2) \\
p(\hat{s} = s_2) &= 0.2 \times 0.5 = 0.1 \\
\xi_{s_3} &= a \land -b \land (-x_1 \lor x_2) \\
p(\hat{s} = s_3) &= 0.8 \times 0.5 = 0.4 \\
\xi_{s_4} &= -a \land -b \\
p(\hat{s} = s_4) &= 0.2 \times 0.5 = 0.1
\end{align*}
\]

Let \( h = x_1 \rightarrow x_2 \), where \( Q = \{x_1, x_2\} \),
\[
H = N_Q(h) = \{(1,1), (0,1), (0,0)\}.
\]

By theorem 1, it leads to a believe potential with focal \( F_1 = \{(1,1), (0,1), (0,0)\} \),
\[
F_2 = \{(1,1), (0,1), (1,0), (0,0)\}.
\]

Then
\[
\begin{align*}
[q(F_1)]_m &= p(s_1) + p(s_2) + p(s_3) = 0.9 \\
[q(F_2)]_m &= p(s_4) = 0.1
\end{align*}
\]

Thus
\[
dsp(x_1 \rightarrow x_2, \xi) = [\varphi^+ Q(H)]_m = \sum_{F_i \in H} [q(F_i)]_m = 0.9.
\]

It might be interesting to look again at the example 2.

**Example 2** We suppose that three computers \( x_1, x_2 \) and \( x_3 \) are connected as shown in Figure 2. Other conditions are the same as Example 1.

\[
\begin{array}{c}
\xrightarrow{a} \\
\xrightarrow{b}
\end{array}
\]

Fig. 2 Three computers are connected

Similar to example 1, we can construct PAS where \( A = \{a, b\} \), \( P = \{x_1, x_2, x_3\} \). There are four scenarios \( s_1 = (1,1), s_2 = (0,1), s_3 = (1,0), s_4 = (0,0) \). The knowledge base \( \xi \) consists of 4 rules of the form \( \xi_1 = (x_1 \land a) \rightarrow x_2, \ xi_2 = (x_1 \land b) \rightarrow x_2, \ xi_3 = (x_2 \land a) \rightarrow x_3, \ xi_4 = (x_2 \land b) \rightarrow x_3 \), i.e.,
\[ \xi = \xi_1 \land \xi_2 \land \xi_3 \land \xi_4 \]  
Let us compute \( dsp(x_1 \rightarrow x_3, \xi) \).

The knowledge base \( \xi \) can be transformed into an equivalent set of clauses:

\[ \Sigma = \{-x_1 \lor -a \land x_2, -x_1 \lor -b \land x_2, -x_2 \lor -a \land x_1, -x_2 \lor -b \land x_1\} \]

As a consequence, we have:

\[ \xi_{e-x_1} = a \land b \land (-x_1 \land x_2) \land (-x_2 \land x_3) \]
\[ \xi_{e-x_2} = -a \land b \land (-x_1 \land x_2) \land (-x_2 \land x_3) \]
\[ \xi_{e-x_3} = a \land -b \land (-x_1 \land x_2) \land (-x_2 \land x_3) \]
\[ \xi_{e-x_4} = -a \land b \land x_1 \land x_2 \land x_3 \]

\[ p(\hat{s} = s_1) = 0.4 \quad p(\hat{s} = s_2) = 0.1 \]
\[ p(\hat{s} = s_3) = 0.4 \quad p(\hat{s} = s_4) = 0.1 \]

Let \( h = x_1 \rightarrow x_3 \), then

\[ Q = \{x_1, x_3\} \]
\[ H = H_{\xi}(h) = \{(1,1), (0,1), (0,0)\} \]

By Theorem 1, this leads to a belief potential \( \varphi \) with focal sets \( FS(\varphi) = \{F_1, F_2\} \) where

\[ F_1 = \{(1,1), (0,1), (0,0)\} \]
\[ F_2 = \{(1,1), (0,1), (1,0), (0,0)\} \]

Then

\[ [\varphi(F_1)]_m = p(s_1) + p(s_2) + p(s_3) = 0.9 \]
\[ [\varphi(F_2)]_m = p(s_4) = 0.1 \]

Thus

\[ dsp(x_1 \rightarrow x_3, \xi) = [\varphi(H)]_b = [\varphi^+(H)]_b = \sum_{F \subseteq H} [\varphi(F)]_m = 0.9 \]

From above two examples, we find that \( dsp(x_1 \rightarrow x_3, \xi) \) is the same as \( dsp(x_1 \rightarrow x_3, \xi) \). Similarly, we can also get the same conclusion if four computers or more are connected. Obviously, this conclusion is absurd. The reason resulting in this conclusion is that believe potential which is constructed in Theorem 1 such that \( H_\xi(h) \) may lose some valuable information. Particularly, the more information in \( \xi \), the more information will be lost. In order to avoid losing information, a new combination algorithm based on evidence theory is introduced in the following section.

III. COMBINATION ALGORITHM OF PAS

The main idea of this algorithm as follows. A big PAS can be divided into several small PAS, every small PAS lead to different believe potentials, combine these potentials in the same space by extension, we can get the degree of support of \( h \) relative to \( \xi \). The algorithm bases on the validity of the decomposition model with conjunction of multi-atomic sets [8].

Then the combination algorithm involves the following five steps:

Step 1: Decompose \( \Sigma \) into smaller parts \( \Sigma_i (i = 1, 2, \ldots, n) \) where \( \Sigma_i (i = 1, 2, \ldots, n) \) are weak-dependent each other.

Step 2: Construct PAS \( (\Sigma_i, A, P, \Pi) \) \( (i = 1, 2, \ldots, n) \) where \( A' \subseteq A, P' \subseteq P, \Pi' \subseteq \Pi \).

For each \( (\Sigma_i, A, P, \Pi) \), we can derive corresponding potentials \( \varphi_i (i = 1, 2, \ldots, n) \).

Step 3: Extend \( \varphi_i (i = 1, 2, \ldots, n) \) on \( P \).

Step 4: Combine each \( \varphi_i (i = 1, 2, \ldots, n) \) to get \( \varphi \), i.e., \( \varphi \otimes \varphi_2 \otimes \ldots \otimes \varphi_n = \varphi \).

Step 5: Compute \( dsp(h, \xi) = [\varphi(H)]_b \), where \( H = H_{\xi}(h) \).

Example 3 The same as Example 2.

Construct PAS, where \( A = \{a, b\} \),
\[ P = \{x_1, x_2, x_3\} \], the knowledge base \( \Sigma \) is given by
\[ \Sigma = \{-x_1 \lor -a \land x_2, -x_1 \lor -b \land x_2, -x_2 \lor -a \land x_1, -x_2 \lor -b \land x_1\} \]

Step 1: Decompose \( \Sigma \) into \( \Sigma_1 \) and \( \Sigma_2 \) where
\[ \Sigma_1 = \{-x_1 \lor -a \land x_2, -x_1 \lor -b \land x_2\} \]
\[ \Sigma_2 = \{-x_2 \lor -a \land x_1, -x_2 \lor -b \land x_1\} \]

atom(\( \Sigma_1 \)) = \{a, b, x_1, x_2\}
atom(\( \Sigma_2 \)) = \{a, b, x_2, x_3\}

Step 2: Construct two smaller PAS \( (\Sigma_1, A_1, P_1, \Pi_1) \) and \( (\Sigma_2, A_2, P_2, \Pi_2) \). In the first PAS \( (\Sigma_1, A_1, P_1, \Pi_1) \) , \( A_1 = \{a, b\} \), \( P_1 = \{x_1, x_2\} \), \( \Pi_1 = \{0, 0.5\} \), the knowledge base \( \Sigma_1 \) is given by
\[ \Sigma_1 = \{-x_1 \lor -a \land x_2, -x_1 \lor -b \land x_2\} \], there are four
scenarios $s_1 = (1,1)$, $s_2 = (0,1)$, $s_3 = (1,0)$, and $s_4 = (0,0)$. By theorem 1, it can lead to a potential $\psi_i$ with focal sets $FS(\psi_1) = \{F_1,F_2\}$, where

$$F_1 = \{(1,1),(0,1),(0,0)\}$$

$$F_2 = \{(1,1),(0,1),(1,0),(0,0)\}$$

$$[\psi(F_1)]_m = p(s_1) + p(s_2) + p(s_3) = 0.9$$

$$[\psi(F_2)]_m = p(s_4) = 0.1.$$ 

Similarly, in the second $PAS(\Sigma_2, A_2, P_2, \Pi_2)$,

$$A_2 = \{a,b\}, \quad P_2 = \{x_2,x_3\},$$

$$\Pi_2 = \{0,0.8,0.5\}, \quad \text{the knowledge base } \Sigma_2 \text{ is given by}$$

$$\Sigma_2 = \{-x_2 \vee -a \wedge x_3, -x_2 \vee -b \wedge x_3\}.$$ 

There are also four scenarios $s'_1 = (1,1)$, $s'_2 = (0,1)$,

$s'_3 = (1,0)$, and $s'_4 = (0,0)$, it leads to potential $\psi_2$ with focal sets $FS(\psi_2) = \{F'_1,F'_2\}$, where

$$F'_1 = \{(1,1),(0,1),(0,0)\}$$

$$F'_2 = \{(1,1),(0,1),(1,0),(0,0)\}$$

$$[\psi(F'_1)]_m = p(s'_1) + p(s'_2) + p(s'_3) = 0.9$$

$$[\psi(F'_2)]_m = p(s'_4) = 0.1.$$ 

Step 3: Extent $\psi_1$ and $\psi_2$ on $P = \{x_2,x_3\}$.

Denote

$$X_1 = F_1^{\land P} = \{(1,1),(1,0),(0,0),(0,1),(1,1),(0,1),(0,0)\}$$

$$X_2 = F_2^{\land P} = \{(1,1),(1,0),(0,1),(1,1),(0,1),(0,0),(0,0)\}$$

$$X_3 = F'_1^{\land P} = \{(0,1),(1,1),(1,0),(0,0),(0,1),(0,1),(0,0)\}$$

$$X_4 = F'_2^{\land P} = \{(0,1),(1,1),(1,0),(0,0),(1,0),(1,0),(0,1)\}$$

Then

$$[\psi_1(X_1)]_m = 0.9 ,$$

$$[\psi_2(X_2)]_m = 0.1 ,$$

$$[\psi_1(X_3)]_m = 0.9 ,$$

$$[\psi_2(X_4)]_m = 0.1 .$$ 

Step 4: Combination.

$$[\psi(X_1 \land X_3)]_m = [\psi_1 \otimes \psi_2(X_1 \land X_3)]_m = 0.81$$

$$[\psi(X_1)]_m = [\psi_1 \otimes \psi_2(X_1)]_m = 0.9 \times 0.1 = 0.09$$

$$[\psi(X_3)]_m = [\psi_1 \otimes \psi_2(X_3)]_m = 0.9 \times 0.1 = 0.09$$

$$[\psi(X_4)]_m = [\psi_1 \otimes \psi_2(X_4)]_m = 0.1 \times 0.1 = 0.01$$

Step 5: Compute $ dsp(x_1 \rightarrow x_3, \xi) = [\psi(H)]_m = \sum_{X \in H, X \notin FS(\psi)} [\psi(X)]_m = 0.81$  

where

$$H = \{(1,1),(0,1),(1,1),(0,0),(0,0),(0,0)\}.$$ 

The merit of combination after extension is that information will not lose. From the degree of support of Example 3, the result is reasonable.

IV. CONCLUSION

Dempster-Shafer theory can be considered as a tool for efficient quantitative computations in probabilistic argumentation systems. But the system would result in losing some valuable information in the course of transformation. In order to overcome this shortcoming, this paper adopts a new combination algorithm which can avoid losing information. Example 3 demonstrates that the combination algorithm is effective.

REFERENCES


