

A proposed Framework for Information Fusion and Obtain Beliefs from Evidences

¹Tamer. M. Abo Neama, ²Ismail. A. Ismail, ³Tarek. S. Sobh and ⁴M. Zaki

¹Military Technical College

²Arab Academy for Science, Technology and Maritime Transport

³Information Systems Department, Egyptian Armed Forces

⁴Azhar University

Tamer_abonema@yahoo.com, Ismail.ghafar@aast.edu, tarek voice@yahoo.com, azhar@enu.eg

Abstract

Information fusion is an advanced research area which can assist decision makers in enhancing their decisions. This paper aims at designing a new multi-layer framework that can support the process of performing information fusion and obtaining beliefs from evidences.

In this framework the bottom layer consists of multiple sources of textual data. Then a Multi-Agent System, MAS platform is utilized to afford the following agents (ordered bottom up):

1. A communication agent that communicates with the data sources to obtain relevant topics.
2. A data integration agent which integrates the collected data in one file.
3. A parsing agent that forms syntactic structures based on an arbitrary set of predefined tokens (keywords).
4. An agent to create a semantic network based on a slot-filling mechanism in order to associate concepts and attributes to their values.
5. A belief computation agent that finds out the basic belief assignments.

Keywords : *Information Fusion, Multi-Agent System MAS, Dezert – Smarandache Theory DSMT, Semantic networks, Belief combination.*

1. Introduction

The need for timely and accurate processing of large amounts of uncertain and possibly incomplete data from multiple dissimilar sources is felt in many industrial and defense contexts. Most of the time, the fusion of information coming from the multiple sources is being manually performed by the operators/users. This process of manually and mentally re-plotting information by the staff and the commander is complex, time consuming and prone to error [1]. Furthermore, the amount and complexity of information now available has made this type of data fusion impractical and the situation is worsening as new surveillance sources become available.

The management and combination of uncertain, imprecise, and even paradoxical or highly conflicting sources of information has always been, and still remains today, of primal importance for the development of reliable modern information systems involving artificial reasoning.

The fusion of information arises in many fields of applications nowadays (especially in defense, medicine, finance, geo-science, economy, etc). When several sensors, observers or experts have to be combined together to solve a problem, or if one wants to update his current estimation of a solution for a given problem with some new information available, a solid mathematical tool is needed for the fusion process, especially when the information is imprecise and uncertain.

To deal with such situation an information fusion and obtain beliefs from evidences framework has been designed. At the bottom level such framework is concerned with data collection level, this task can be conducted by search engines, wireless sensor networks or software agents. The proposed system employs a multi-agent system, MAS platform to collect data from multiple sources [2]. The next level is concerned with data processing where natural language processing, text retrievals, or syntactic structures can be used. The proposed framework obtains the required structure syntactically using a combination of text scanner and morphological parser. The third level is information organization; this task may be carried out using either rule based clustering or semantic networks (frames) [3]. Our system utilizes semantic networks to provide properly a slot filling mechanism. Accordingly, the underlying values are related to their attributes.

The theory of evidence (Dempster-Shafer) has been proposed [4] as a promising avenue in combining information coming from different sources in the particular objective of target identification and decision making. However, one major inconvenient of the combination rule used in this theory (Dempster's rule) lies on the exponential increase of the number of propositions (focal elements). This number becomes rapidly unmanageable causing a serious problem for real-time applications. In addition such Dempster-Shafer rule cannot deal with conflicts of data. Therefore, at this level Dezert-Smarandache theorem, DS_mT has been relied on to deal with realistic situations and to obtain hypothetical beliefs.

The paper is organized as follows: Section 2 explains the related work to the proposed framework, while section 3 presents the problem statement. Section 4 expresses the details of the proposed framework. Section 5 presents the belief computations using DS_mT. Section 6 discusses the results of an experimental case study. Finally, section 7 comprises the conclusion.

2. Related Work

Information fusion (IF) is defined as the combination of data from disparate sources to produce an outcome that is superior to any provided by an individual source. An outcome typically includes an improvement in accuracy, higher confidence through complementary information, or improved performance in the presence of countermeasures. IF can occur on multiple levels.

Sensor-level fusion is the level at which relevant data is extracted from the source signal. *Feature-level fusion* is the combination of data to produce a composite feature vector that characterizes the object under test.

The Joint Directors of Labs (JDL) have developed the most prominent model of information fusion. The JDL fusion model and its revisions [5] focus on maximizing the automation of fusion. It breaks data fusion into five levels, each of which further refines the data from the acquired state to a form that both adequately represents the entities and their environment and is actionable.

Much of the literature surrounding IF focuses on the various levels of the JDL model to create and optimize algorithms that merge sensor data in a complex and dynamic space. Automated target location, identification, and tracking are central themes in this type of fusion. It is obvious that the concept of information fusion could be employed in different applications. These applications include military systems, identification systems, and intelligent analysis systems.

2.1 Military Systems

Defining a sensor network ontology [6], taking into account the relations of target attributes that appear in the real world, represents a key to deduct some of the target features, based on the observations of another ones. If done properly, it may resolve most of the fusion problems that occur in real situations. However, if information gathered from the observation means is ambiguous, the usability of the ontology fusion is substantially sacrificed. In such cases the application of DS_mT, [7] seems to be an excellent solution. The same authors [8] have extended their work by making use of a concept called 'intelligent consultant' that is means which provides the command and control system operator with a support in the case when the gathered information is incomplete, imprecise or even conflicting.

The authors of [9] propose design and implement a hierarchical Multi Agent based Information Fusion System for Decision Making Support (MAIFSDMS). The information fusion is implemented by applying Maximum Score of the Total Sum of Joint Probabilities (MSJP) fusion method and is done by a collection of Information Fusion Agents (IFA) that forms a multiagent system. MAIFS uses a combination of generalization of Dasarathy and Joint Director's Laboratory (JDL) process models for information fusion mechanism. Information fusion products that are displayed in graphical forms provide comprehensive information regarding the Military Operation, MO's area dynamics. By observing the graphics resulted from the information fusion, the commandant will have situational awareness and knowledge in order to make the most accurate strategic decision as fast as possible.

2.2 Analysis and identification systems

The works of [1] and [10] have analyzed an identification algorithm in the evidence theory framework. The identification algorithm is composed of four main steps:

- (1) Sensor reports are transformed into initial Basic Probability Assignments, BPA.
- (2) The successive BPAs are combined through Dempster's rule.

- (3) The resulting BPAs are approximated to avoid algorithm explosion.
- (4) In parallel to step (3) a decision is taken on the identification/classification of an object from a database which is based on the maximum of pignistic probability criterion.

Also those authors performed an identification analysis and proposed an error measure based on the distance between the approximated function and the original one (without approximation). This distance provides a means to quantify the quality of the approximation.

2.3 Intelligent analysis systems

Ensuring the accuracy of intelligence assessments is made difficult by the pervasiveness of uncertainty in intelligence information and the demand to fuse information from multiple sources. The works of [12] and [13] have described a tool named Infusion, as model-based software for information fusion and uncertainty assessment in intelligence analysis. In this tool the process for information fusion and analysis is based on a model that consists of two basic activities:

- **Collection:** the analyst extracts facts from intelligence documents or sources;
- **Inference:** the analyst evaluates the facts to determine the existence of threats in the environment.

3. Problem Statement

The obvious problem of situation analysis is the existence of data/information processing levels that should be covered. At the bottom level large volumes of data from different sources will have to be processed in order to achieve high level decisions. Classical and manual evaluation followed by the presentation of results is much too time consuming. It is therefore important to identify key issues by using data and information fusion techniques to find methods to give automated support to information and data collected from multiple sources in order to become more efficient beliefs and consequently decisions.

The basic elements of the underlying framework are pointed out as follows:

- 1) Given multiple sources $S_1, S_2 \dots S_i \dots S_n$; $1 \leq i \leq n$, where S_i contains a set of facts $\Theta = \{\theta_{i1}, \theta_{i2} \dots \theta_{ij} \dots \theta_{ik}\}$; where $1 \leq j \leq k$. Sources may be either people (individuals or organizations) or documents.
- 2) Use an information fusion agent to obtain hypothetical beliefs, $m(\cdot)$ from the available data using DSMT, taking into consideration the constraint:

$$m(\emptyset) = 0, \sum_{\emptyset \subseteq \Theta} m(\emptyset) = 1$$

4. The Proposed Framework

A new multi-layer framework is proposed here in order to support the process of performing information fusion and obtaining beliefs from evidences, as shown in Figure (1).

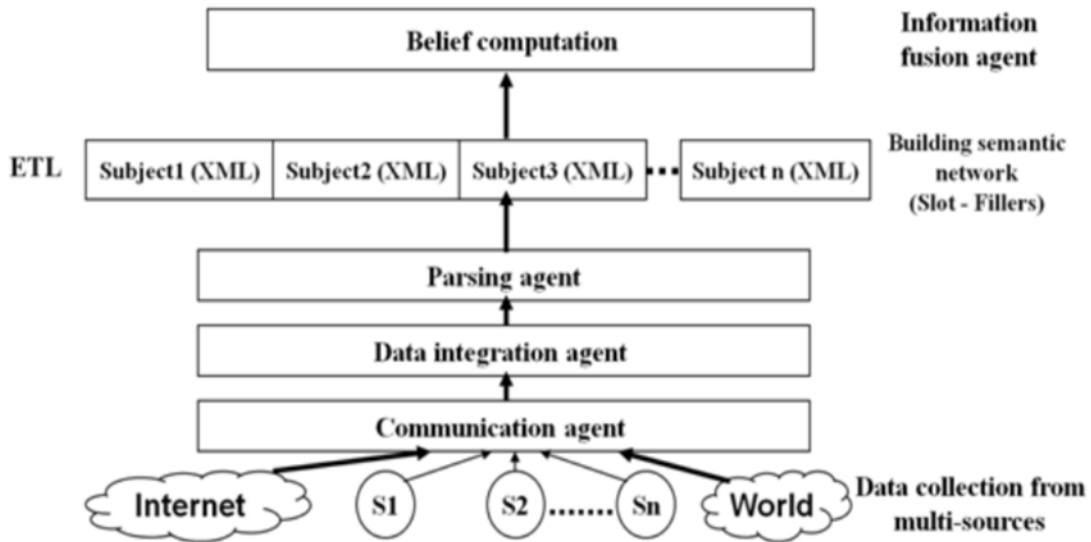


Figure (1) The proposed framework

This framework aims at providing a cause from the corresponding events.

To fulfill such aim it consists of multi-layers that can support this process. The relations between the proposed framework components are pointed out in the following:

1) Data sensors

To collect raw data different sources are exploited that range from S_1 to S_n , Figure (2). Here, data means facts, figures, and other relevant materials, that can serve for both study and analysis. However the underlying module is concerned only with textual unstructured data available from the Internet.

Data needed for our proposed model can be broadly classified into:

- (a) Data pertaining to humanbeings,
- (b) Data relating to organizations, and
- (c) Data pertaining to territorial areas

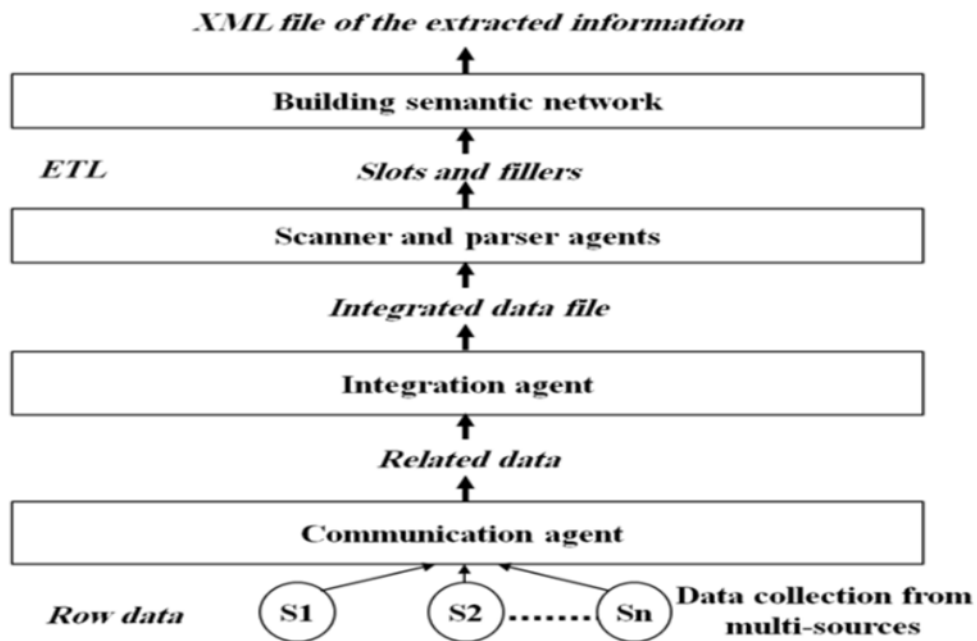


Figure (2) Process model of the proposed framework

Multi-agent system

The multi-agent system, MAS view represents an advantageous paradigm for the analysis, design and implementation of complex software systems. It proposes powerful metaphors for information system conceptualization, a range of new architectures, techniques and technologies specifically destined for large scale distributed intelligent systems [2].

The MAS component of the proposed framework consists basically of three essential agents. From bottom up, the first one is a communication agent that reads data from sensors relates them and produces clusters of related data. The second one is an integration agent that takes such related data from multiple files and produces a single integrated data file. The third one is a parsing agent that scans the integrated data file, extracts tokens and builds up a tree structure around the obtained tokens. In addition the parser agent discovers the attributes in the input text and the corresponding values in order to provide the slots and fillers needed for constructing the semantic network.

2) Semantic network

It provides a slot filling mechanism on the basis of the slots and fillers that have been obtained from the multi-agent system. Accordingly, such component extracts useful information by linking fillers (arcs) with the relevant slots (nodes). The output is an XML file containing the extracted information.

5. Belief Computation using DS_mT

The Shafer's model, [14], on which is based the Dempster-Shafer Theory, assumes an exhaustive and exclusive frame of discernment $\Theta = \{\theta_1, \theta_2, \dots, \theta_n\}$ of the problem under consideration. The model requires actually that an ultimate refinement of the problem is possible so that the focal element θ_i can always be well precisely defined in such a way that we are sure that they are exclusive and exhaustive. From this model, a Basic Belief Assignment (bba), has a function $m(\cdot) : 2^\Theta \rightarrow [0, 1]$ such that $m(\emptyset) = 0$ and

$$\sum_{A \in \mathcal{P}} m(A) = 1$$

Where A represents an element of Θ and every $m(A)$ is associated to a given body of evidence where 2^Θ denotes the set of all subsets of Θ . Within DST, the fusion (combination) of two independent sources of evidence is obtained through the Dempster's rule of combination [14]:

$[m_1 \oplus m_2](\emptyset) = 0$ and $\forall B \neq \emptyset \in 2^\Theta$:

$$[m_1 \oplus m_2](B) = \frac{\sum_{X \cap Y = B} m_1(X) m_2(Y)}{1 - \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y)} \quad (1)$$

The notation $\sum_{X \cap Y = B}$ represents the sum over all $X, Y \in 2^\Theta$ such that $X \cap Y = B$. The Dempster's sum $m(\cdot) \triangleq [m_1 \oplus m_2](\cdot)$ is considered as a basic belief assignment if and only if the denominator in equation (1) is nonzero. The term $k_{12} \triangleq \sum_{X \cap Y = \emptyset} m_1(X) m_2(Y)$, is called degree of conflict between the sources B_1 and B_2 .

The DST, although very attractive because of its solid mathematical ground, it includes several weaknesses and limitations because of the Shafer's model itself (which does not necessary hold in some fusion problems involving continuous and ill-defined concepts). Actually, Dempster's rule fails when the conflict between sources becomes important.

To overcome such limitation, Jean Dezert and Florentin Smarandache [15] proposed a new mathematical theory based on other models (free or hybrid DS_m models) with new reliable rules of combinations able to deal with any kind of sources (imprecise and uncertain, i.e. highly conflicting).

5.1 The free DS_m model

The foundation of the DS_mT is to abandon the above Shafer's model (i.e. the exclusivity constraint between θ_i of Θ) because for some fusion problems it is impossible to define the problem in terms of precise and exclusive elements. The free DS_m model, denoted

$M^f(\Theta)$, on which is based DSMT allows us to deal with imprecise notions and concepts between elements of the frame of discernment Θ . The DSMT includes the possibility to deal with evidences arising from different sources of information which do not have access to absolute interpretation of the elements Θ under consideration.

From this idea and from any frame Θ , a new hyper power set $D^\Theta = \{\alpha_{d0}, \dots, \alpha_{d(n)-1}\}$ by the following rules:

- 1- $\emptyset, \theta_1, \theta_2, \dots, \theta_n \in D^\Theta$
2. $\forall A \in D^\Theta, B \in D^\Theta, (A \cup B) \in D^\Theta, (A \cap B) \in D^\Theta$
3. No other elements belong to D^Θ , except those, obtained by using rules 1 or 2.

5.2 Classic DSMT rule of combination

This approach allows us to model any source which supports paradoxical (or intrinsic conflicting) information. From this simple free DSMT model $M^f(\Theta)$, the classical DSMT rule of combination $m(\cdot)$, $[m_1 \oplus \dots \oplus m_k](\cdot)$ of $k \geq 2$ intrinsic conflicting and/or uncertain independent sources of information is defined by [16]

$$m_{\oplus}([m_1, \dots, m_k])(A) = \prod_{i=1}^k m_i(X_i) \quad (2)$$

where $m_{\oplus}(\emptyset) = 0$ and

$$\sum_{A \in D^\Theta} m(A) = 1$$

5.3 Notion of hybrid model

The adoption of the above free DSMT model (and the classic DSMT rule) versus the Shafer's model (with the Dempster's rule) can also be subject to criticisms since not all fusion problems correspond to the free DSMT model (neither to the Shafer's model). These two models can be viewed actually as the two opposite/extreme. In general, the models for characterizing practical fusion problems do not coincide neither with the Shafer's model nor with the free DSMT model. They have a hybrid nature (only some θ_i are truly exclusive).

A hybrid DSMT model M is defined from the free DSMT model $M^f(\Theta)$ by introducing some integrity constraints on some elements $A \in D^\Theta$, if there are some certain facts in accordance with the exact nature of the model related to the problem under consideration [15]. An integrity constraint on $A \in D^\Theta$ consists in forcing A to be empty through the model M , denoted as $m \equiv \emptyset$. There are several possible kinds of integrity constraints introduced in any free DSMT model. Examples of these constraints are listed in the following:

- Exclusivity constraints: when some conjunctions of elements of Θ are truly impossible, for example when $\theta_{\square} \cap \dots \cap \theta_{\square} \stackrel{M}{=} \emptyset$.
- Non-existential constraints: when some disjunctions of elements of Θ are truly impossible, for example when $\exists \emptyset \square \theta_{\square} \cup \dots \cup \theta_{\square} \stackrel{M}{=} \emptyset$
- Hybrid constraints: like for example $(\theta_1 \cap \theta_2) \cup \theta_k \stackrel{M}{=} \emptyset$ and any other hybrid proposition/element of D^{Θ} involving both \cap and \cup operators such that at least one element θ_k is subset of the constrained proposition.

The introduction of a given integrity constraint $\exists \emptyset \in D^{\Theta}$ implies the set of inner constraints $B \stackrel{M}{=} \emptyset$ for all $B \subset A$. The introduction of two integrity constraints on $A, B \in D^{\Theta}$ implies the constraint $(A \cup B) \in D^{\Theta} \equiv \emptyset$ and this implies the emptiness of all $C \in D^{\Theta}$ such that $C \subset (A \cup B)$.

5.4 The hybrid DS_m rule of combination

The hybrid DS_m rule of combination, associated to a given hybrid DS_m model $M \neq M_{\emptyset}$ for $k \leq 2$ independent sources of information is defined for all $A \in D^{\Theta}$ as [15]:

$$m_{M(\Theta)}(A) \triangleq \emptyset(A) [S_1(A) + S_2(A) + S_3(A)] \quad (3)$$

where $\emptyset(A) = 1$ if $A \notin \emptyset$ and $\emptyset(A) = 0$ otherwise. Here is the set of all elements of D^{Θ} which have been forced to be empty through the constraints of M .

$S_1(A)$, $S_2(A)$, and $S_3(A)$ are defined by

$$S_1(A) \triangleq \sum_{\substack{X_1, X_2, \dots, X_k \in D^{\Theta} \\ X_1 \cap X_2 \cap \dots \cap X_k \square A}} \prod_{\substack{\theta_i \in \Theta \\ \theta_i \square X_i}} \text{mass}(\theta_i) \quad (4)$$

$$S_2(A) \triangleq \sum_{\substack{X_1, X_2, \dots, X_k \in \emptyset \\ [u \square A] \vee [(u \in \emptyset) \wedge (A \square I_t)]}} \prod_{\substack{\theta_i \in \Theta \\ \theta_i \square X_i}} \text{mass}(\theta_i) \quad (5)$$

$$S_3(A) \triangleq \sum_{\substack{X_1, X_2, \dots, X_k \in D^{\Theta} \\ X_1 \cup X_2 \cup \dots \cup X_k \square A \\ X_1 \cap X_2 \cap \dots \cap X_k \in \emptyset}} \prod_{\substack{\theta_i \in \Theta \\ \theta_i \square X_i}} \text{mass}(\theta_i) \quad (6)$$

Where $u \triangleq u(X_1) \cup u(X_2) \cup \dots \cup u(X_k)$ and $u(X)$ is the union of all θ_i that compose X , $I_t \triangleq \theta_1 \cup \theta_2 \cup \dots \cup \theta_n$ is the total ignorance. $S_1(A)$ corresponds to the classic DS_m rule, $S_2(A)$ represents the mass of all relatively and absolutely empty sets which is transferred to the total or relative ignorance associated with non existential constraints and $S_3(A)$ transfers

the sum of relatively empty sets directly onto the canonical disjunctive form of non-empty sets.

5.5 The information fusion algorithm

The above calculations could be exploited to compute final beliefs by making use of an algorithm that contains the following steps, as shown in Figure (3):

- 1- Extract relevant evidences from the available data by making use of a semantic network slot-filling mechanism.
- 2- Calculate the basic belief assignments, bba's, from evidences.
- 3- Depending on the underlying model nature, whether free or hybrid, make the necessary branching.
- 4- If the model is free, calculate classic DSsm belief, $m_{DSsmC}(\cdot)$.
- 5- On the other hand, if the model is hybrid, calculate $m_{DSsmC}(\cdot)$ followed by the proportional conflict redistribution to yield $m_{PCR}(\cdot)$.

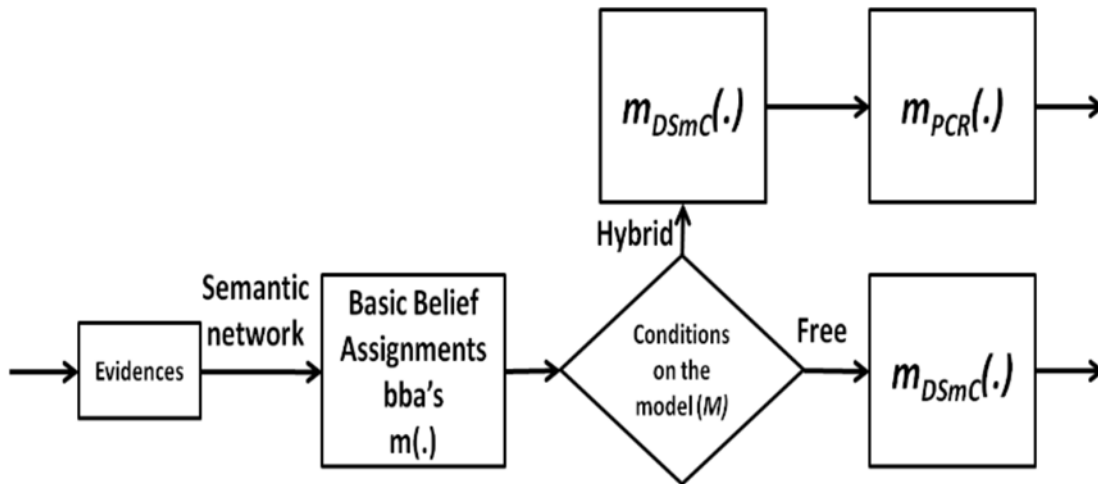


Figure (3) The information fusion algorithm

6. Case Study

6.1 Experimental setup

Figure (4) presents the environment (hardware, software, and the connection) of the implementation of the proposed model.

Its configuration can be described as follows:

1- Hardware Configuration

- a. Server machine
 - i. Intel XEON dual core processor

- ii. 4GB RAM
- iii. 2 x 750GB HD
- iv. Ethernet
- b. client machine
 - i. Intel Core 2 Duo
 - ii. 2 GB RAM
 - iii. 80 GB HD
 - iv. Ethernet
- c. Ethernet router
- d. Internet connection.

2- Software configuration

- a. Server machine
 - i. OS: windows server for server machine
 - ii. NetBeans IDE 7.0.
 - iii. java development kit 1.6.
 - iv. JADE agent software.
 - v. GeNIe 2.0 (Bayesian network decision system)
- b. client machine
 - i. OS : windows 7 for client machine.
 - ii. java development kit 1.6.
 - iii. JADE agent software.

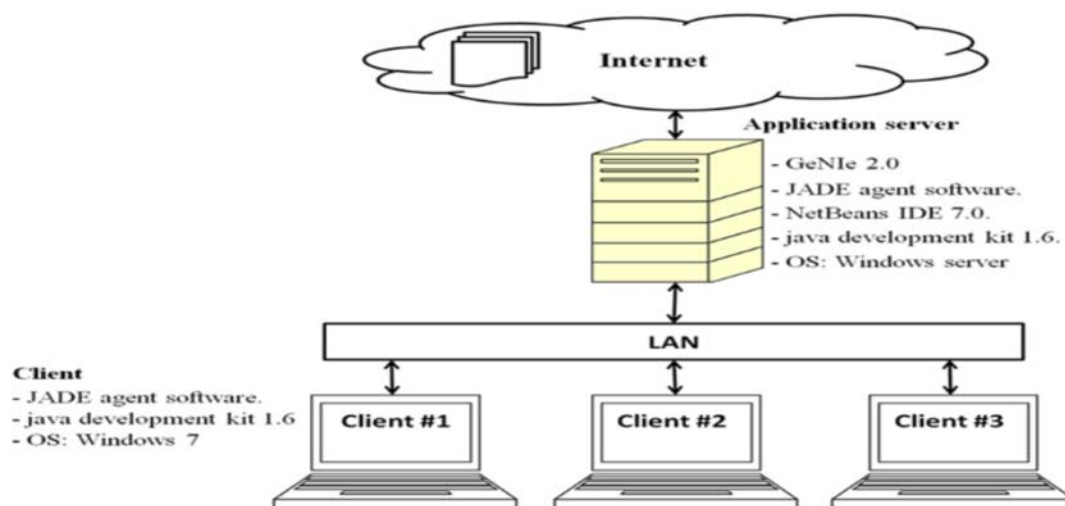


Figure (4) The laboratory configuration setup

6.2 Case study details

This case study describes a typical attack event that may be carried out by three attackers in a popular location (hotel). The victim is denoted by V and he is killed in the attack. There are mainly two sources of information, namely, S1 and S2, where S1 represents Arabic sources (text documents) and S2 represents foreign sources.

The authorities of the victim nation are interested in:

- 1- Finding out the guilty persons.
- 2- Discovering the motivating organization.

The solution of this case study could be obtained using the following procedure:

6.2.1 The solution procedure

- 1- **Data collection:** Data is collected from the available online news papers and Internet documents. For convenience, such data is clustered into two clusters; the first one is belonging to S1 while the second is belonging to S2. The news of the attack are published in the media throughout several textual documents which indicated that:
 - a- Three men (Daniel, Paul, and Stephan) denoted here by D, P, and S respectively, are the suspected persons to murder V.
 - b- According to the available news documents and collected data from different sources, there is a solid relation between Stephan and Paul.
- 2- **Semantic network construction:** The slot filling mechanism of the proposed model has been used to construct the semantic network shown in Figure (5). In that semantic network counting slots are utilized in order that the number of instances of an object can denote the basic belief in its occurrence. A particular basic belief is increased by repetition and is calculated from Shafer formula [15]:

$$\text{Belief} = \text{Belief} + \text{Default_Value} (1 - \text{Belief})$$

Where, $0 \leq \text{Default_Value} \leq 1$

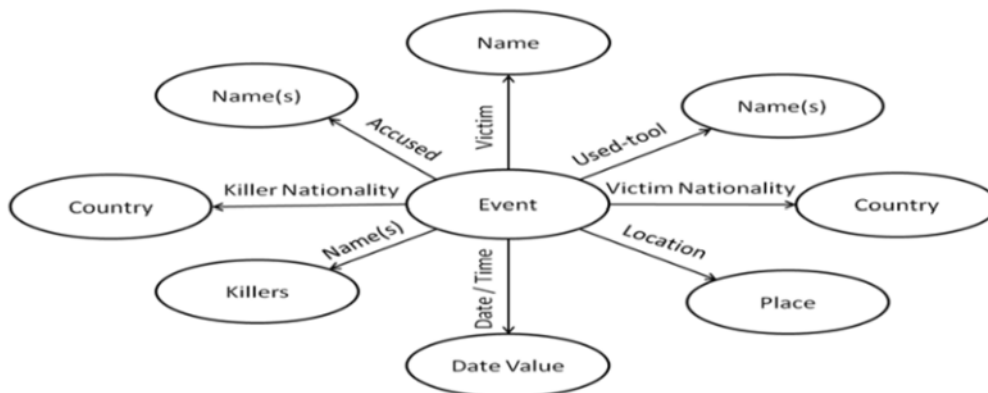


Figure (5) Semantic network for the case study

3- **Basic belief assignment:** The problem for such attack can be represented by the frame of discernment $\Theta = \{\theta_1, \theta_2, \theta_3\}$, where θ_1, θ_2 , and θ_3 are the hypotheses D, P, and S respectively. Since the data has the constraint that both S and P are related (intersected) then the free model of Shafer [15] cannot be applied. Instead, the DS_m hybrid model, denoted by DSh_m is applicable. According, by considering the two information sources, S1 and S2 and exploring the semantic network module for both of them, we could construct the following:

Table (1) Basic belief assignment (bba's) for case study

	D	P	S
m (S1)	0.3	0.7	0.0
m (S2)	0.4	0.0	0.6

Where $m (S_i), i=1, 2$ represents the basic belief assignment (bba's), of the underlying information source.

4- **Application of the hybrid model:** The choice of the DS_m hybrid model allows some intersections to be exist while others are empty. Thus $P \cap S \neq \emptyset$ while $D \cap P = D \cap S = D \cap P \cap S = \emptyset$

Table (2) Classic DS_m belief in the case study

	θ_1	θ_2	θ_3	$\theta_1 \cap \theta_2$	$\theta_1 \cap \theta_3$	$\theta_2 \cap \theta_3$	$\theta_1 \cap \theta_2 \cap \theta_3$
	D	P	S	$D \cap P$	$D \cap S$	$P \cap S$	$D \cap P \cap S$
m_{DSmC}	0.12	0	0	0.28	0.18	0.42	0

These values are obtained from DS_mT for combining bba's so that:

- $m(\emptyset) = 0$.
- $\text{DSh}_m(\theta_i) = m_{1c}(D) * m_{2c}(D)$ (similarly for P and S).
- $\text{DSh}_m(P \cap S) = (m_{1c}(P) * m_{2c}(S)) + (m_{2c}(P) * m_{1c}(S))$ (similarly for $m_{2c}(\cdot)$)
- $\text{DSh}_m(D \cap P \cap S) = (m_{1c}(D) * m_{1c}(P) * m_{1c}(S))$ (similarly for $m_{2c}(\cdot)$)
- And, $\sum_{A \in \Theta} \text{DSh}_m(A) = 1$, where Θ is the space of beliefs i.e. $A \in \{D, P, S, D \cap P, D \cap S, P \cap S, D \cap P \cap S\}$.

Depending on the classic DS_m beliefs, a proportional conflict redistribution is performed to yields m_{PCR5} as illustrated in Table (3)

- 5- **Proportional conflict redistribution:** To execute proportional conflict redistribution PCR, we transferred $m_{DsmC}(D \cap P) = 0.28$ to D and P and $m_{DsmC}(D \cap S) = 0.18$, to D and S proportionally:

Table (3) Proportional conflict redistribution for the case study

	D	P	S	$D \cap P$	$D \cap S$	$P \cap S$	$D \cap P \cap S$
m_{PCR}	0.282	0.178	0.120	0.000	0.000	0.420	0.000

This means that Dsm model has a belief of 0.42 that both P and S have been cooperated to conduct the attack and to assassinate V.

6.3 Comparative study

A comparative study of the proposed framework with other information fusion systems is illustrated in Table (4). This comparison as such, has pointed out the significance of the proposed framework features. These features confirm the fact that such framework represents a complete realization for all the model layers, Figure (1). This ensures its superiority to support the process of performing information fusion and obtaining beliefs from evidences. In this comparative study the proposed framework is compared with the identity fusion algorithm [1] and the multi-agent information fusion system [9].

Table (4) Comparative study between the proposed framework and other information fusion systems

Model Property	The proposed framework	Identity fusion algorithm [1]	Multi-Agent Information Fusion Systems [9]
Main application area(s)	- Anti-terrorism - Spy war - Security negotiations	Direct fleet support scenarios where raw data reports are time dependent	Military operations
The information fusion technique	Use of Dezert Smarandache Theory, DSMT. Actually, DSMT is applicable for “both” free and hybrid models that permit Θ_i 's of Θ to be intersected.	Use of Dempster Shafer theory of evidence for combining information coming from different sources. This theory is applicable “only” for free models in which Θ_i 's of Θ should be exclusive and exhaustive.	The theory of evidence is not taken into consideration; consequently, no beliefs are calculated to be relied upon. Information fusion is based on the JDL model that has been carried out in four levels.
The data collection Technique	By making use of MAS platform (JADE).	The algorithm is concerned only with the process of information fusion.	Utilize an Information Fusion Agent, IFA which consists of five supporting agents.
The role of the system agents	1- Data collection. 2- Data integration. 3- Parsing the integrated file 4- Creating a semantic network 5- Estimating the basic belief assignments	No software agents are used.	Intelligent Agent, Operation Agent, Personnel Agent, Logistic Agent, Communication Electronics (Comlec) Agent, in addition to one Main Agent
Information organization	Use of semantic network with a slot-filling mechanism in order to associate values to concepts and attributes.	Data is organized to substitute the algorithm parameters.	Utilization of a hierarchical multi-agent based system.
Evidence based reasoning	Can obtain the reason behind the believed hypothesis.	Cannot obtain the reason behind the believed hypothesis.	Does not depend on beliefs and does not use any evidence theory.

From Table (4) it is obvious that:

1. The use of DS_mT for information fusion yields not only more realistic beliefs but also reliable pignistic probabilities for the underlying propositions i.e. the management of information is carried out on two levels. The credal level during the combination of beliefs and the pignistic level that supports decision making.
2. The use of MAS platform can provide easy way for data collection, flexible communications and better automation.
3. The features of the proposed architecture confirms the fact that it out performs other similar situation awareness systems.

7. Conclusion

It is not an easy task to cross the gap between evidences and beliefs, the proposed framework consists of several layers goes up from raw data to belief computation in order to provide a suitable architecture. The bottom layer consists of multiple sources of textual data. Then a Multi-Agent System, MAS platform is utilized to afford the following agents (ordered bottom up):

1. A communication agent that communicates with the available data sources to obtain relevant topics and subjects.
2. An integration agent who integrates the collected data in one unstructured data file.
3. A parsing agent that forms syntactic structures based on an arbitrary set of predefined keywords.
4. An agent to create a semantic network based on a slot-filling mechanism in order to associate values to concepts and attributes.
5. A belief computation agent that estimates the basic belief assignments.

A case study is investigated in details. It has proved the concept of the proposed framework and indicated the following:

1. The use of DS_mT for information fusion yields not only more realistic beliefs but also reliable pignistic probabilities for the underlying propositions i.e. the management of information is carried out on two levels. The credal level during the combination of beliefs and the pignistic level that supports decision making.
2. The integration of the information fusion and the Bayesian network by exploiting the pignistic probability. By this way we could provide probabilistic inference and enable decision making on the basis of both belief based probabilities for the underlying propositions and Bayesian based probabilities for the corresponding reasons.
3. The use of MAS platform can provide easy way for data collection, flexible communications and better automation.

References

- [1] A.-L. Jusselme, E. Bossé, and A. Jouan, “Analysing an identity information fusion algorithm based on evidence theory”, the RTO IST Symposium on Military Data and Information Fusion, held in Prague, Czech Republic, pp. 13-1 – 13-32, October 2003. Available at <http://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA428563>.
- [2] V.Gorodetsky, O.Karsaeyv, and V.Samoilov, “Multi-agent Data and Information Fusion: Architecture, Methodology, Technology and Software Tool”, St. Petersburg Institute for Informatics and Automation of the Russian Academy of Sciences, Vol. 198, pp. 308- 347, 2003.
- [3] John F. Sowa, “Semantic networks”, in Stuart C. Shapiro, ed. Encyclopedia of Artificial Intelligence, Second Edition, Volume 2. New York: John Wiley, pp. 1493-1511, 1992.
- [4] E. Bossé and M.-A. Simard, “Managing Evidential Reasoning for Identity Information Fusion,” Society of Photo-Optical Instrumentation Engineers, Vol. 37, pp. 391–400, 1998.
- [5] K. Weise and W. Wöger, “A Bayesian Theory of Measurement Uncertainty”, Meas. Sci. Technol., Germany, 1993.
- [6] M. Chmielewski, R. Kasprzyk, “Usage and characteristics of ontology models in Network Enabled Capability operations”, MCC Conference, Cracow, 2008.
- [7] Florentin Smarandache, Jean Dezert, “Advances and Applications of DSMT for Information Fusion”, Vol 2, pp. 3-38, American Research Press Rehoboth, 2006.
- [8] Ksawery Krenc, Adam Kawalec, “An improvement of C2 systems performance using DSMT and ontology fusion approaches”, R&D Marine Technology Centre, Dickmana, WAT Military University of Technology, Kaliskiego, Warsaw, Poland, 2010.
- [9] Sumari, A.D.W., and Ahmad, A.S., “Design and Implementation of Multi Agent-based Information Fusion System for Supporting Decision Making (a Case Study on Military Operation)”, ITB Journal of Information and Communication Technology, Institut Teknologi Bandung, Bandung, pp. 42-63, 2008.
- [10] A. L. Jusselme, D. Grenier, and E. Bossé, “Analyzing approximation algorithms in the theory of evidence,” in Sensor Fusion: Architecture, Algorithms and Applications VI (P. of SPIE, ed.), Vol. 4731, (Orlando, FL), pp. 65–74, 2002.
- [11] Klir, G. and M. Wierman, “Uncertainty-Based Information: Elements of Generalized Information Theory”, 2nd edition, Physica-Verlag, pp.168, 1999.
- [12] Kari Chopra, Craig Haimson, “Information Fusion for Intelligence Analysis”, Proceedings of the 38th Hawaii International Conference on System Sciences, pp. 111a-111a, 2005.
- [13] Clark, R.M., “Intelligence Analysis: Estimation and Prediction”, Baltimore, MD: American Literary Press, 1996.
- [14] G. Shafer, “A mathematical theory of evidence”, Princeton University Press, 1976.
- [15] F. Smarandache and J. Dezert, "The Combination of Paradoxical, Uncertain, and Imprecise Sources of Information based on DSMT and Neutro-Fuzzy Inference", Proceedings of 10th International Conference on Fuzzy Theory and Technology (FT&T 2005), Salt Lake City, Utah, USA, July, 2005.
- [16] Dezert J., “Foundations for a new theory of plausible and paradoxical reasoning”, Information & Security, An international Journal, edited by Prof. Tzv. Semerdjiev, CLPP, Bulg. Acad. of Sciences, Vol. 9, pp. 13-57, 2002.

