Multi-Level Information Fusion and Active Perception Framework: Towards a Military Application

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ABSTRACT

Situation Awareness, as the perception of the environment and its elements with respect to time and space, has to deal with more and more heterogeneous information. This diversity leads to new challenges in Information Fusion such as combining the processing of both Hard (physical sensors) and Soft (human reports and knowledge databases) data.

Hard & Soft Information Fusion implies various issues. First, the information representation must be versatile enough to cope with such a large variety of observations and object descriptions. Second, the dynamic dimension of Situation Awareness must be considered and handled by a model.

Moreover, in the specific case of crisis situations, the frequency of information acquisition is a key factor to assess a situation, which can be achieved by understanding what element is important to observe and to recognize. Besides, the available resources (e.g. sensors) are limited and could be dependent on each other in their use. For all these reasons, there is a need to develop an intelligent system to support decision-making by automating the sensor management.

This paper presents a multi-level Information Fusion framework based on Dynamic Bayesian Networks (DBN) extended with an active perception approach. This framework offers a formalization of the environment as a causal graph of variables and an information gain function to evaluate the reliability of each variable. The reliability score enables the Most Valuable Variables (MVVs) to be identified in the DBN, towards maximizing the gain of information about the situation. Finally, the complexity of the inference is reduced by working on DBNs reduced to these MVVs. The final step is dedicated to the selection of sensors maximizing the coverage of the MVVs.

The main contribution consists in evaluating this system in a realistic and credible military scenario as a proof of concept. This scenario pictures a military offensive to invade a region and our framework is used to estimate the strategy the enemy will use during its attack based on the type and capacity of its troops and their movements. Thanks to our system, hypotheses are formulated to the user about the enemy presence and its intentions. This work is supported by the French MoD (DGA).

1.0 INTRODUCTION

Situation Awareness (SA) [1][2] goes through complex difficulties as sensors are more and more diversified. Multi-Intelligence is a new challenge to assess a situation in a High-Level understanding.

Among these problems, the representation of such a disparity of information is prevailing. Retrieved information can be divided into two parts. First, the Hard data provided by physical sensors (camera, radar, sonar, …) which inform on the quantitative nature of observed objects. Secondly, the Soft data coming from linguistic content (observer report, text, phone call, …) provides qualitative information about these objects and the relations between them. The purpose is to be able to align the representation of these two kind of information.

Besides the representation, the modelling aspect adds the need to combine the collected information to best qualify the observed elements. Providing such a description of a situation allows a temporal monitoring to help a human agent to make a decision.

Yet, another concern is the complexity of objects and their relations evolving in a complex and dynamic world. The impossibility of being omniscient in such an environment causes the necessity to define observation strategies in order to obtain crucial information in a smart way.

Furthermore, in a crisis situation [3], the temporal constraint becomes significantly amplified and the speed of information acquisition and processing becomes a major need in the system. Here, the purpose is to acquire picture of the current state of the situation with a reasonable reliability to help the operator take a prompt and efficient decision.

This difficulty is reinforced by the strong uncertainty due to three factors. The first one is the dynamic dimension of the partially observable environment. The second one comes from the uncertainty inherent to sensors. And the final one results from the information fusion.

All this brings a new need which is not getting a horizontal observation. We mean by horizontal observation the fact that the information is retrieved passively. This way to get observation implies no action on sensors is taken and this strategy tends to monitor the maximum number of objects. This is generally used to leverage the number of objects observed or to detect abnormal behaviour. Some passive approaches have already been proposed (MURI Project [6], Markov Logic Networks [7], Conceptual Spaces [8], Conceptual Graphs [9], ...), but these passive ways of getting information are not efficient enough in a crisis situation with a large amount of heterogeneous sensors.

The specificity of SA in a crisis situation involves the need of a vertical observation. The term vertical means an in-depth observation that aims to observe specific objects that have to be monitored and need to be characterised in an acceptable time.

To address this specific problem, we have developed an active information fusion system which operates on the available sensors corresponding to the active perception [5]. A work has been carried out on the active sensor data selection on object recognition [12]. But it only handles static environment. Another work is on the classification of objects, such as the approach on attentional sequence-based recognition with Markov reasoning [13] or an approach on active object recognition with reinforcement learning [14]. Nevertheless, these works are on a low-level fusion for too specific tasks, and they only manage Hard data with no heterogeneity.

An interesting approach with Dynamic Bayesian Networks (DBN) modelling is the possibility to represent a situation with an active perception method [15]. The main point of this work is to optimise the sensor activation to actively observe the environment. This model is well adapted to work on dynamic environment with an active process on sensors to optimize information gain. Notwithstanding, Hard and Soft data are not delimited and the complexity of the criterion is not sufficient for a near real-time computability.

We propose in this paper to apply our Information Fusion framework with an active perception approach [19] to a military scenario which tends to be credible and realistic on its construction. We present in Section 2 the framework and the environment modelling with DBN and the Most Valuable Variables analysis. Section 3 described the military scenario. Section 4 explains how this scenario is modelled through our framework. Section 4 instantiates the scenario and shows some results. Finally, Section V discusses future work and concludes.

2.0 INFORMATION FUSION FRAMEWORK WITH DBN

Information fusion in SA aims to fuse various collected data to describe a situation with all its elements and their relation [4]. The first part introduces the global concept of the active framework, all its processes and how the environment is modelled with DBN.

2.1 An active Information Fusion framework

Figure 1 shows a chain of processes which describe the active Information Fusion framework. The framework allows to estimate if the knowledge on the situation is enough reliable to help a human operator to take a decision from the environment description.

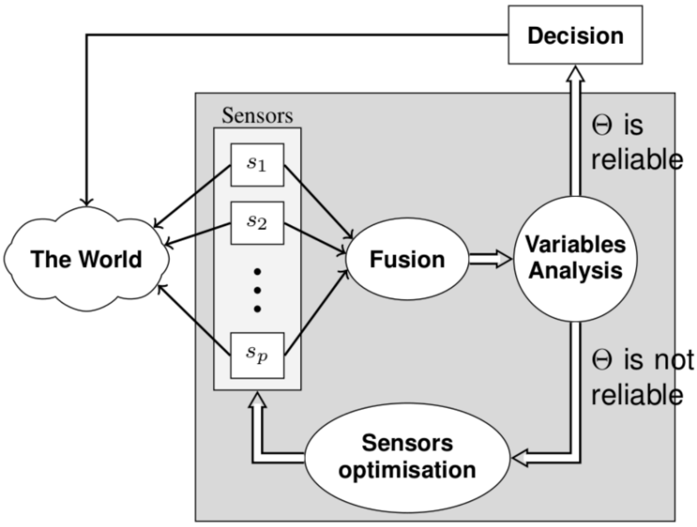

Figure 1: Information Fusion framework overview.

Let consider a set S = <s1, s2, …, sp> of sensors, each either Hard or Soft, observing the world. Each sensor brings an observation on a variable of the world. The resulting observations are sent to a fusion process to define a similarity distance between each observed object to state whether an information describe the same object or not. The result is an aggregated description of objects with their attributes and relations by combining all observations. Several fusion methods exist and there are interesting overviews to compare each one in [10] and [11].

The situation is described with a set of hypotheses Θ on what the world might be at the current time. The variables analysis process then estimate how much each hypothesis states are reliable or not (as described further). If all hypotheses are reliable enough, the framework considers the operator can make a decision with a satisfying belief on the estimated situation. If there is still too much uncertainty, the system decides to ask for new information. To get information in the most efficiently manner, the variable analysis calculates which are the Most Valuable Variables (MVV) to observe to maximise the information gain at the next time step.

Once the system knows what is best to observe in the current situation, the final process optimize the sensors/variables attribution and define the next action of each sensors in the purpose of maximising the coverage of the MVV defined by the previous process. This chain of processes makes the perception active by making the sensor acquisition based both on the quantitative and qualitative cursor.

2.2 Environment modelisation with Dynamic Bayesian Networks

2.2.1 DBN modelisation and inference

The Dynamic Bayesian Networks model is a natural way of modelling a dynamic environment defined by random variables. As pointed in [16], DBN are preferred to Kalman Filter Models (KFM) and Hidden Markov Models (HMM). KFM requires all the Conditional Probability Densities (CPD) to be linear-Gaussian whereas DBN models allow non-linear CPD. HMM has a single random variable as state space when a DBN model has a set of random variables. Moreover, DBN enables a more general topology of graph representations. Finally, DBN naturally represents the spatio-temporal dimension as an extension of Bayesian Networks for dynamic environments.

The temporal dimension is represented by time slices and each time slice is a BN. Each vertex represents a random variable and edges of the graph depict the dependency of a random variable in relation to its parents. As a consequence, the DBN inference differs from the BN inference and is represented by a joint distribution such as:

$$P(X_{1:T}) = \prod_{t=1}^{T}\prod_{i=1}^{n} P\left(X_i^t \,|\pi(X_i^t)\right)$$

Where $\boldsymbol{X_i^t}$ is the $\boldsymbol{i^{th}}$ random variable at time $\boldsymbol{t}$ and $\boldsymbol{\pi(X_i^t)}$ are the parents of the $\boldsymbol{i^{th}}$ random variable at time $\boldsymbol{t}$

and its parent from $\boldsymbol{t-1}$ including itself.

2.2.2 Hypothesis through DBN

As said previously, in Situation Awareness, the aim is to assess a situation through a dynamic environment. Here the environment is defined with a set of hypothesis $\Theta = <\theta_1,..., \theta_p>$ where θ_i depicts the elements which need to be monitored (Figure 2 left).

Figure 2 (right) shows the model of a hypothesis (takes over the work in [15]) which is described by variables divided in two sets. The observable variables set $I = < I_1, I_2, ..., I_m >$ can be observed by sensors. The inferable variables set $X =< X_1, X_2, ..., X_n >$ cannot be observed, but inferred from variables in I which describe the variable X_i. Each variable in X is described by one or more variables in X or in I.

This network also represents a set of sensors is represented as $S = <s_1, s_2, ..., s_p>$. An edge connects a variable and a sensor if the sensor s_i can observe a variable I_j by one of its possible actions. An action could be a physical movement (moving a camera, orientating a radar, …) as well as an algorithm applied on the sensor (object recognition, tracking, …).

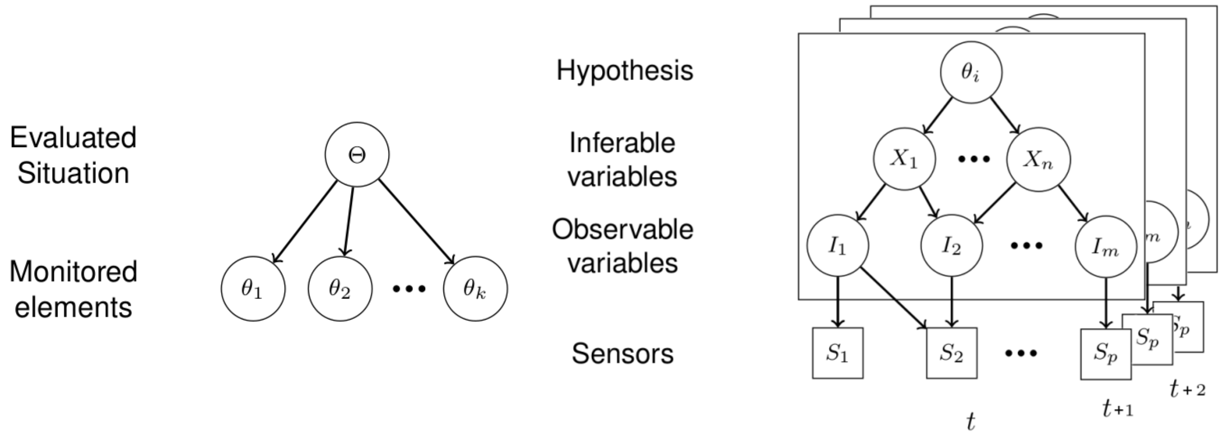

Figure 2 : Hypothesis representation with DBN

2.3 Most Valuable Variables analysis

As the final aim is to get a sufficient reliability on each hypothesis in Θ, and knowing that each θ is a random variable of the DBN, the first step of this process is to determine if the situation is known with enough reliability. To achieve this, the system uses a global threshold of reliability under which a random variable is not considered as having enough reliability. Each random variable has a reliability score. If the score of each hypothesis is greater or equal to the reliability threshold, then the belief state of the situation is considered sufficient to make a decision. Otherwise, the system must analyse which variables are the most valuable to reach this confidence.

Let Γ denote the global threshold of reliability and $\gamma(X)$ the reliability score of a random variable X (and for $\gamma(\theta)$ a hypothesis). Since a DBN is composed of random variables, the natural way is to use the Shannon entropy [17] [18] on the probability distribution of x as an uncertainty measure, as follows:

$$H(X) = -\sum_{t=1}^{n} P_i \log P_i$$

The Shannon entropy is then normalised by the number of possible states of the random variable X denoted n as:

$$\gamma(X) = -\frac{H(X)}{-\log(n)}$$

The closer to zero the reliability score is, the more the state of the random variable is considered known. The final aim is to have all hypotheses in Θ with a score $\gamma(\theta) < \Gamma$.

Let $V = <v_1, v_2, \ldots, v_l>$ be the set of MVV. As the active perception seeks to optimise sensors observation, an important point to notice is only observable variables in I can become valuable variables. Firstly, the process computes the score for all variables in X. In the first case, if $\gamma(X) < \Gamma$, there is no reason to observe its parents, thus no observable variables which describe them. But if the reliability is not sufficient, the system checks the next parent reliability score and so on. If the uncertainty of the last parent in X is not reliable, then the observable variables that describe it become valuable variables. The set of variables V is a subset of I as each MVV resulting from this process is an observable variable.

Figure 3 depicts this process in a theoretical example. In this example, the inferable variable X_3 is considered reliable by its score, so the observable variable I_1 is not interesting anymore to observe. In contrast, the variables I_2 and I_3 become valuable variables since for both, the inferable variable they describe is not reliable.

Once the set of MVV is defined, the sensors are orientated to obtain the best coverage of them. And all variables $\notin V$ are considered not worth observing. This focus on MVV allows to save resources and to maximise the information gain on the next time step.

To maximise the information gain, the naive concept here is to choose the less reliable one as the priority variable to observe. For each variable $\in V$, the algorithm chooses the best sensors able to observe the variable and assigns it. The best sensor for a variable is considered to be the sensor with the best precision to observe this variable.

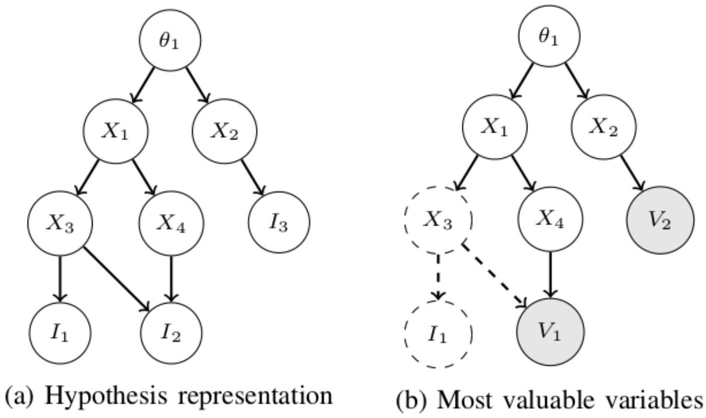

Figure 3: MVV analyses process example

3.0 OPERATIONAL SCENARIO DESCRIPTION

A military scenario has been defined to test this active perception framework in a credible and plausible way. The purpose is to represent a battlefield during an offensive operation to demonstrate the capability to assess a situation and help in decision making in order to prepare a counter-offensive.

The scenario opposes a country *A* which will be invaded by the enemy represented by the country *B* (as shown in Figure 4). Knowing this threat, intelligence from country *A* has defined different High Priority Information Zones (HPIZ) which represent the waypoints where enemy’s troops can cross. Thus, the HPIZ correspond to the point on the map where sensors will try to retrieve information for the purpose of defining the strategy of the enemy.

The strategy of the enemy is defined by which zone the enemy will attack. As shown in Figure 4, there are four possible attack points (AP) for the enemy to reach the border and go through the allied troops of the country *A*. To assess the enemy's strategy, the system should detect and characterise the threat and be able to understand the phase of the attack. Once the framework figures out the strategy, the operator is able to take a decision on how position ally troops to optimise the counter-offensive.

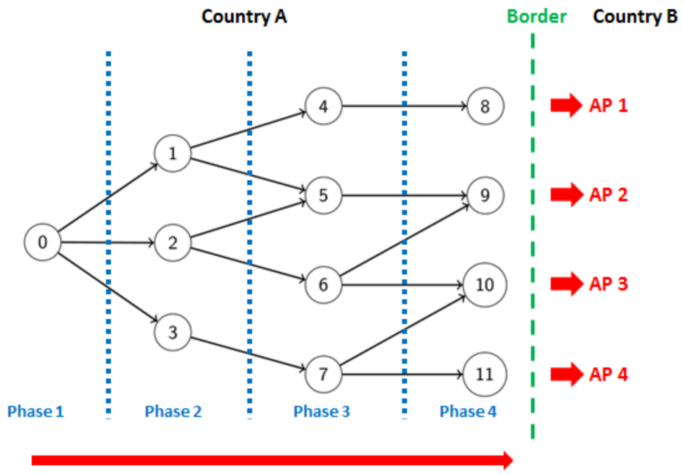

Figure 4 : Global map with HPZI, phases and Attack Point

The intelligence services used to define HPIZ on a battlefield map to determine which zones could bring the best information to understand enemy's manoeuvre and identify the threat. Figure 4 shows a map with HPIZ (numbered nodes) and path between them to represent the possible movements of enemy's troops. The idea in this scenario is to determine which attack point the enemy is choosing to reach by observing these pre-set zones.

To define the strategy of the enemy and which path will be chosen, it is necessary to formalise and represent the threat. The objective is to observe each HPIZ to assess their threat and make projection of possible evolutions of the threat through the different paths. This will lead to a probability for each attack points of being reached by the enemy's troops and considered as the main attack point.

A set of heterogeneous sensors composed by four major intelligence sources is at disposal to observe the HPIZ. The Human Intelligence (HUMINT), the Radar Intelligence (RADINT), the Electromagnetic Intelligence (EMINT) and the Image Intelligence (IMINT) with drones and finally an information system which could request a database. A sensor corresponds to a company from one of these intelligence sources and is defined by constraints and specificities to qualify the threat on a HPIZ.

Although this scenario tends to be credible and plausible, the current maturity of the proposed framework forces to simplify the possibilities and does not permit to take into account all the parameters. For that reason, it is considered here that the enemy wants to reach a unique attack point. This second hypothesis means the enemy does not try to deceive the country *A*. Another constraint is the enemy can only move forward with no turn back. These limits are discussed in the conclusion part.

4.0 SCENARIO MODELLING

This part explains how the presented scenario is modelled through the framework to work on Most Valuable Variables.

4.1 Definition of hypothesis

The hypothesis here is to define by which attack points the enemy will pass to lead its assault. This could be inferred by knowing by which HPIZ the main threat is prone to pass. The hypothesis θ_{AP} is described by a probabilities distribution with a set of possible states. The states are all possible attack points, so here $< AP_1, AP_2, AP_3, AP_4 >$. This hypothesis is described by a set of inferable variables themselves described by observable variables as shown in Figure 5.

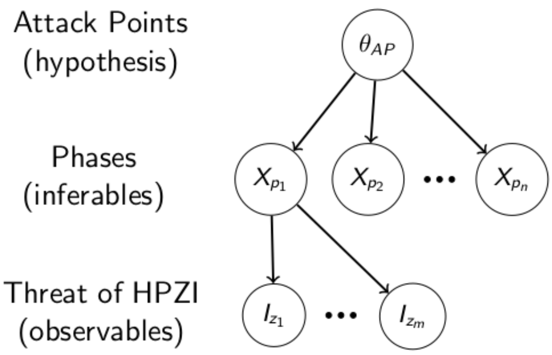

Figure 5 : Global hypothesis description

The first inferable random variables which allow to infer the hypothesis are the different phases of the attack. A phase is given by the intelligence services with the HPIZ. A phase is considered here as a set of HPIZ representing the progress of the assault. The random variable of a phase X_{p_i} has a set of possible HPIZ as probabilities distribution. In this scenario, the possible state of the random variable X_{p_1} is $< HPZI_1, HPZI_2, HPZI_3 >$ describing the probabilities that the threat go through the HPIZ 1, 2 or 3 during the phase 1.

Finally, the observable variables in this scenario are the HPIZ as we can observe and qualify the threat they represent. For the readability, we consider 4 possible states for each HPIZ as $< high\ threat, medium\ threat, low\ threat, no\ threat >$. This is a simplified scale of threat but it is possible to represent it through a score from 1 to 100 discretised with a more or less high granularity.

4.2 Formal modelling of the threat

The threat is considered in regards to the troops present in a HPIZ. The troops are defined by the companies of the adversary army. Each company represent a greater or lesser threat according to its role during an assault. Reasonably, a company of tanks represents a major threat compared to an artillery company as tanks are used to break through the defense lines so they are more representative of the path the enemy will take to reach the attack point.

Hence, to represent the threat of a HPIZ, a score is defined for each kind of company. A tank company represent a score of 5, an infantry company a score of 3 and an artillery company a score of 1. The scenario focuses only on these 3 types of company but it could handle others like armoured artillery, motorized infantry or reconnaissance company. The threat is evaluated by the sum of all present companies and then normalised by the attack phase where the HPIZ belongs to.

More formally, when a HPIZ is observed, its threat is considered known on the threat scale previously defined by a sum of all companies threat normalized on the scale. But for non-observed HPIZ, the system uses a propagation of the threat through all other HPIZ. This is calculated such as:

$$P(I_{HPIZ_i} = x) = \alpha \sum_{I_{HPIZ_j} \in u(I_{HPIZ_i})} P\left(I_{HPIZ_j} = x\right) . P\left(I_{HPIZ_i} \mid I_{HPIZ_j}\right) \qquad \mathbf{(1)}$$

Where $P\left(I_{\mathrm{HPIZ}_i} = x\right)$ is the probability for I_{HPIZ_i} to be at the state x and $P\left(I_{HPIZ_i} \mid I_{HPIZ_j}\right)$ is the probability for the threat to propagates from I_{HPZI_j} to I_{HPZI_i} knowing I_{HPZI_j} is one of the parents of I_{HPIZ_i} (denoted $u(I_{HPIZ_i})$). The probability is computed for each state of I_{HPIZ_i} allowing one to derive the normalisation α.

The threat score is then normalised compared to all HPIZ in a same phase of attack. This allows us to calculate the probability of X_{p_m}, corresponding to the inferable random variable of the phase m. The threat score is defined as:

$$P\left(X_{p_m} = I_{HPIZ_i}\right) = \frac{TA_{HPIZ_i}}{\sum_{HPIZ_j \in \pi(u(HPIZ_i))} TA_{HPIZ_i}} \qquad (2)$$

With TA_{HPIZ_i} the threat assessment score of the $HPIZ_i$, $u(HPIZ_i)$ all the parents of $HPIZ_i$ and $\pi(u(HPIZ_i))$ all the children of parents of $HPIZ_i$. This probability is computed on each I_{HPIZ_i} belonging to the phase m.

Finally, the probability of each attack point AP_l describing the hypothesis θ_{AP} is calculated as:

$$P(\theta_{AP} = AP_l) = \alpha \prod_{I_{HPIZ_i} \in u(AP_l)} \sum_{I_{HPIZ_j} \in u(I_{HPIZ_i})} P\left(X_{p_m} = I_{HPIZ_i}\right) . P(I_{HPIZ_i} \mid I_{HPIZ_j}) \qquad (3)$$

The probabilities resulting from this are then shown as the probability of the enemy to attack each point on the map at each time step. An important note is all variables take into account the state of the previous time step, but it is not shown here for readability reasons.

5.0 INSTANTIATION AND RESULTS

This section introduces a brief example based on the military scenario. The idea is to show the different time step and the interest of MVV through the proposed modelling. The Figure 6 on the left represents the map of the instantiated scenario where each node is a HPIZ. The Figure 6 on the right described the hypothesis on the attack points θ_{AP}. Enemy troops are attacking from the node zero to reach one of the attack points. The reliability threshold is defined as $\Gamma = 0.20$. The Figure 7 shows the evolution of reliability score of each variable (hiding 4th iteration for readability purpose).

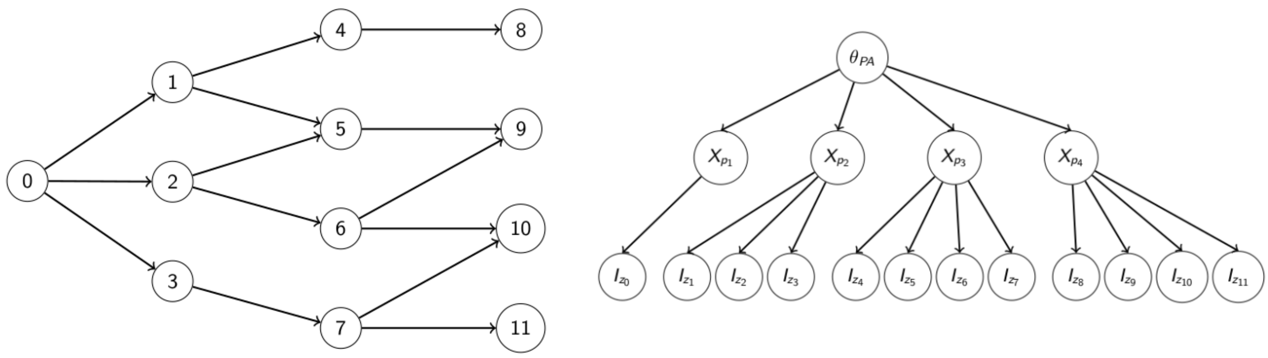

Figure 6: (left) HPIZ map description of the military scenario. (right) hypothesis description.

This example points out several important remarks. As it is represented at t_1 where the scenario starts after the observation of the three HPIZ of the phase one $< I_{HPIZ_1}, I_{HPIZ_2}, I_{HPIZ_3} >$, the state of each HPIZ is considered reliable enough, but it does not allow to discriminate efficiently the phase as $\gamma(X_{p_1}) > \Gamma$. These three HPIZ are not observed at the next step, which results by the decreasing of the reliability making HPIZ 1 and 2 worth to observe again.

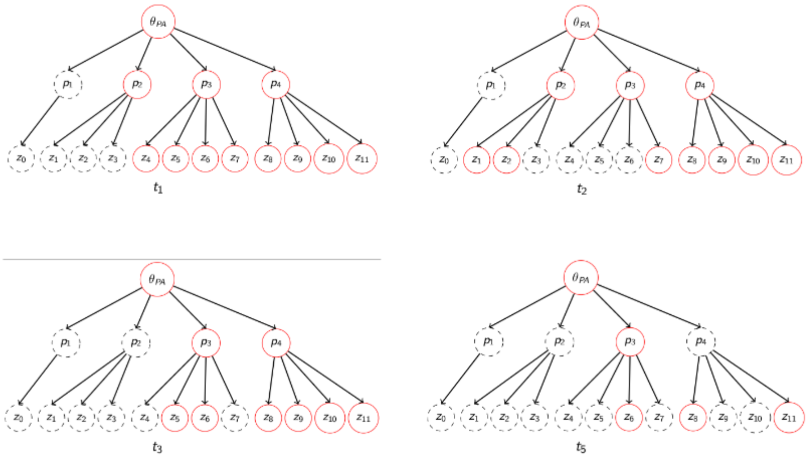

Figure 7: Time step progression: dashed nodes are reliable variables and red nodes are MVV (each graph are the same as Fig. 6 right)

Table 1: (left) Reliability $\gamma(x)$ score of the hypothesis and phases at each time step. (right) Sensors group attribution on MVV

	t_1	t_2	t_3	t_4	t_5
θ_{AP}	0.96	0.66	0.35	0.27	$\emptyset$
θ_{p_1}	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$	$\emptyset$
θ_{p_2}	0.35	0.47	$\emptyset$	$\emptyset$	$\emptyset$
θ_{p_3}	0.97	0.43	0.41	0.36	0,26
θ_{p_4}	0.96	0.62	0.44	0.22	$\emptyset$

Sensor groups	t_1	t_2	t_3	t_4
Group 1	$HPZI_6$	$HPZI_7$	$HPZI_{10}$	$HPZI_{10}$
Group 2	$HPZI_4$	$HPZI_2$	$HPZI_5$	$HPZI_9$
Group 3	$HPZI_5$	$HPZI_1$	$HPZI_9$	$HPZI_5$

The result of the third step shows another interesting point. The HPIZ 8 and 11 are close to be lesser than the threshold only thanks to the inference of the threat despite the fact they were not observed. This shows one of the interests of MVV analysis as the system saves resources by not observing every variable while being able to increase reliability on these non-observed variables. Now, the first phase is considered known but not the phase 2 and 3. Nevertheless, the system starts to picture the strategy of the enemy as the probabilities of the attack point are more and more accurate.

Finally, at the last iteration, the next observations enable the framework to estimate the attack point with enough reliability. The most interesting point here is the system was able to perform this inference whereas one phase and three HPIZ are considered not reliable. This highlights the fact that the system doesn't need to observe each observable variables to define the enemy's strategy. Being able to determinate which variable could bring higher information quantity save resources and iteration of observation.

Table 2: Evolution of probability for each Attack Points (AP)

Attack points	t_1	t_2	t_3	t_4
$P(\theta_{AP} = AP_1)$	0.181	0.151	0.088	0.008
$P(\theta_{AP} = AP_2)$	0.366	0.498	0.87	0.945
$P(\theta_{AP} = AP_3)$	0.272	0.294	0.085	0.042
$P(\theta_{AP} = AP_4)$	0.181	0.057	0.013	0,005

Through this example, the system offers a first optimisation thanks to the MVV analysis. The most informative HPIZ were defined and it led to increase significantly the reliability on the hypothesis. Furthermore, the framework presented the probability of each attack point through the entire scenario at each time step given by the Equation 3 (as shown on Table 2). Even before the knowledge on the hypothesis is considered reliable, an operator could see the evolution of each probability to try to assess the situation.

6.0 FUTURE WORK AND CONCLUSION

Situation Awareness through High-Level Information Fusion represents significant challenges. The modelling is one of them and must represent a situation in its completeness as much as possible. However, other constraint of calculability makes it difficult and forces to simplify problems. The challenge is to find the good balance to produce a sufficient system to assess a situation to help an operator to take decisions.

The scenario proposed here is a first version to test the modelling of the presented Active Information Fusion framework. The aim was to verify is this modelling is compatible with intelligence methods during a battlefield to assess the strategy of the enemy. This first version is promising but requires some improvements to be more realistic and tested with more complex strategies.

The next steps is firstly to add complexity the scenario as to taking into account the possibility of a company to turn back or to a path between two HPIZ to be broken like a bridge being destroyed. Another important step is to propagate the belief on probabilities distribution of each random variable automatically. Several possibilities exist and have to be tested. Finally we also think about other hypothesis to monitor as the enemy army description by the companies observed to define which battalion or division we are facing to.

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