Conflicts Resolution and Situation Awareness in Heterogeneous Multi-agent Missions using Publish-subscribe Technique and Inferential Reasoning

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Keywords: Multi-agent Reasoning, Bayesian Networks, Multi-agent Learning, Publish-subscribe, Heterogeneous Multi-agent Coordination, Cooperative Perception.

Abstract: In this paper, we propose a priority-based publish-subscribe approach to tackle reasoning in beliefs conflicts for a heterogeneous multi-agent mission. Agents subscribe to other agents' topics and rank them based on agents' situation awareness. Bayesian Belief Network (BBN) was used in maintaining agents' belief and recorded mission information could be used for the BBN training using conjugate gradient descent or expectation-maximization algorithms. The output of the training is the learned network for agents' predictions, estimations, and conclusions. We also propose an agent's self presumption inferential reasoning where agents learned heuristics and used them for future inferences. We test the system by using a team of heterogeneous Unmanned Aerial Vehicles (UAVs) with different sensor profiles and capacities tasked together to perform forest fire searching. To verify belief and settle conflicts, agents follow these steps: sequentially assess the prioritized publish-subscribe topics, inferential reasoning using the learned network, inferential reasoning using logical propositions, and learning process. From our experiment, the BBN training and prediction perfection grow up with the increase in the number of training data. Future work focuses on obtaining the optimal number of samples needed for effective prediction, effective agents' beliefs merging, communication protocol, and bandwidth utilization.

1 INTRODUCTION

The heterogeneous multi-agents mission comprises of a team of different agents with different beliefs (sensor data), roles, and capacities tasked collectively to achieve a particular goal. It has a potential advantage of categorizing agents' based on their specialization, backup provision, and robustness (Cortés and Egerstedt, 2017; Setter and Egerstedt, 2017; Khan et al., 2015; Setter and Egerstedt, 2017; Yanmaz et al., 2017). For example, consider a team of aerial and grounds robots tasked to conduct forest fire fighting, agents can divide the task into extinguishing, fire spreading monitoring, rescuing, and so on. Use of heterogeneous agents provides a wider opportunity for detecting false alarm due to sensor variation (Merino et al., 2006). For example, agents carrying camera sensors may have different beliefs from agents using object sensors in the vehicle overload detection system. The agents using facial recognition can detect sitting on each other's lap passengers and count them as two, while agents using an object sensor may count it as one passenger. Another agent may use a weight balance sensor to count passengers based on their masses. A challenge arises in merging beliefs derived from different sensors to make an optimal correct decision that will support agents' cost functions. In every multi-agent mission, energy, mission time, communication link, and other resources need to be utilized.

We tackled this problem by applying a priority-based publish-subscribe technique model using Bayesian inferential reasoning and Distributed Situation Awareness (Endsley, 1995; Stanton et al., 2006). The idea is that each agent has its own beliefs. It will then subscribe to other relevant topics. Agent belief variation is sorted out using probabilistic priority value. The probabilistic priority value rises with the number of right decision and agents' situation-awareness (i.e., how agents currently perceive the environment). It changes from agents to agents based on the agents' environmental adaptation because some agents perform better than other agents in different scenes. For example, agents using thermal sensors

Yusuf, S. and Baber, C.
Conflicts Resolution and Situation Awareness in Heterogeneous Multi-agent Missions using Publish-subscribe Technique and Inferential Reasoning.
DOI: 10.5220/0009147408460851
In *Proceedings of the 12th International Conference on Agents and Artificial Intelligence (ICAART 2020) - Volume 2*, pages 846-851
ISBN: 978-989-758-395-7; ISSN: 2184-433X

could perform better than the one using camera sensor in detecting fire during day time because of the possibility of having fire-like terrains (e.g., dried grass). The reverse could be the case when the agents are operating on higher altitudes where heat could not be sensed effectively.

We applied Bayesian Belief Network (Pavlin et al., 2010; Wang and Xu, 2014; Williamson, 2001) in monitoring the agents' beliefs and their causal relationships hard-coded during pre-mission planning. The BBN's nodes are categorized into situation, awareness, and utility nodes in the BBN. The agents' situation nodes are the current belief of the environment. For example, fire present or absenteeism based on sensor information. Awareness node is the confirmed situation; that is decided belief that undergone verification process from different agents using different sensors that, fire is present or not at a particular location. The utility node is a measure of how welcome the agents are with the proposed beliefs. We modelled the agents' utility as Distributed Constraint Optimization (DCOP). DCOP is the behaviour of the agents towards the optimal assignment of their variables with the aim of minimizing cost functions(Fioretto et al., 2018; Fransman et al., 2019; Maheswaran et al., 2004; Zhou et al., 2018).

Every agent has topics to broadcast to the network (i.e., its sensor data) and subscribe to other agents' topics in order to be authenticating its beliefs to a genuine knowledge of the environment. The environment may keep changing, and communication may be limited, which is a potential challenge of such architecture. However, we propose a knowledge-base inferential reasoning and Bayesian learning to solve this issue.

Inferential reasoning allows the agents to predict, estimate, and draw conclusions based on previous experience (Fransman et al., 2019; Wang and Xu, 2014; Williamson, 2001). Bayesian inference computes predictions based on the probabilities of the prior variables using conditional probabilities (Wang and Xu, 2014). Another mode of inferential reasoning we want to discuss is the agents' presumption inference. In this approach, agents build in their knowledge in the form of if-then logical propositions rules, then use that knowledge to make predictions and conclusions. For example, in multi-agent search and rescue missions, if an agent sees its co-agents hovering over a place instead of usual navigation, it can perceive that something interesting is present in that location and act to support that agent.

In this paper, we tackle the problem of agents' belief variation conflict using the publish-subscribe technique. The agents' beliefs are modelled using Bayesian Belief Network, and agents' resource utilization uses DCOP. We propose Bayesian and heuristic-based inferential reasoning in monitoring the agents' belief conflict. We use heterogeneous multi-agent coordination to conduct wildfire monitoring as the use case.

The rest of this paper was organized as follows. Section 2 describes the basics background of publish-subscribe, inferential reasoning, and agents' reasoning towards resource utilization (DCOP). Section 3 describes the related work and summary of our contribution. Section 4 describes the ontology of the systems using forest fire monitoring as the use case and experiments with their results. Finally, section 5 describes the conclusions and future works.

2 BACKGROUND

2.1 Publish-subscribe Multi-agent Interaction

In a multi-agent system, the publish-subscribe technique categorizes the agents into senders (publishers) and receivers (subscribers). Agents subscribe to other co-agents' topics (information) if it is helpful and interesting to them (Hackney and Clayton, 2015; Rivera et al., 2016). Agents might have a maximum number of subscriptions and topics to be broadcast into the network. As such, agents prioritize their publishers based on information saliency and context-awareness (i.e., current environmental situation). Agents use sends and acknowledge protocols to monitor messages delivery and update a list of subscribers (Rivera et al., 2016). That is, agents may change their publishers or subscribers over time based on the environmental changes.

Moreover, the agents' coordination architecture can be centralized or decentralized. In a centralized approach, agents are controlled by a server, as such publishing and subscribing management became easier. The challenges of this approach is that the central server needs much computational power, memory, communication bandwidth, and other resources if the number of agents increases (Cortés and Egerstedt, 2017; Saicharan et al., 2016; Turpin et al., 2014; Vasile and Zuiani, 2011). In a decentralized approach, agents have the full right to control their values and use two types of communications approaches, that is, explicit and implicit messaging (Gerkey and Mataric, 2002). In explicit messaging, agents share information when they are close to each other. In implicit communication, agents do not send messages; rather, they sense other co-agents within a few inches as in swarm of ants, birds, etc. (Ferrante et al., 2015; Reynolds, 1987; Saicharan et al., 2016).

We applied a priority-based multi-agents publish-subscribe model of interactions. Agents subscribe to other co-agents' topics and prioritise its belief on that publisher based on its specialisation, situation-awareness, or data saliency. For example, in fire searching missions by a team of heterogeneous UAVs carrying different sensor profiles. Let us assume the agents are carrying an infrared, thermal, and visual camera to detect the fire. If the agents with thermal sensors subscribe to the agents with infrared and camera sensors, it can be updating their priorities based on the situation awareness (Endsley, 1995; Stanton et al., 2006). During day time (sunny time), information from the agents with visual sensors could have higher priority than the agent with an infrared sensor. However, the reverse is the case during night time. Therefore, Distributed Situation Awareness - DSA (Stanton et al., 2006) changes the agents' data saliency (i.e., their topics priority). The overall architecture was represented in figure 1.

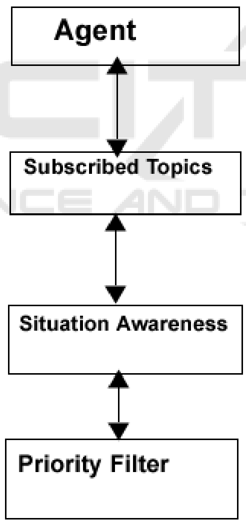

Figure 1: Agents Subscription Layer.

Figure 1 describes the subscription protocol in a top-down passion. We assumed that the agents could access topics and the current environmental condition (situation awareness of the environment). Based on this situation, agents reason and assign priority to topics from their publishers against a hard-corded rule. It means topics priority changes with environmental change. When an agent needs topics from different publishers to verify its belief, priority would be used in making a decision (i.e., making conclusion with the highest priority topics).

2.2 Inferential Reasoning

We assume that the agents are accessible to the global belief based on the Bayesian Belief Network (BBN) of figure 2. They need to verify their beliefs based on that network. We use forest fire detection using heterogeneous UAVs mounted with different sensors as the use case.

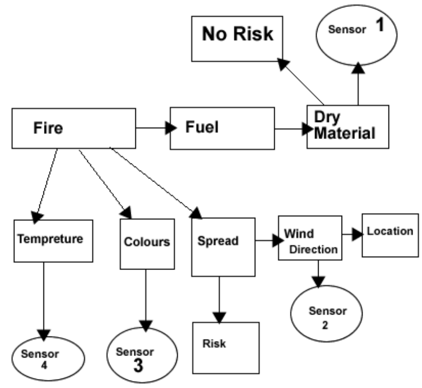

Figure 2: Bayesian Belief Network for Multi-agent Mission.

Figure 2 describes the agents' Bayesian Belief Network for forest fire detection. The system has four different sensors (i.e., dry material, temperature, colour, and wind sensors); agents carrying these sensors broadcast their sensor information (as topics) of which other co-agents can subscribe to for their belief verification. For example, agent using colour (camera) sensor can subscribe to other agents using dry material, wind, and temperature sensors to be verifying its beliefs against false detection e.g., detecting object with the same fire colour palettes. It could be verify simply by using votes technique. Sensor nodes are the situation node, while other nodes (decision nodes) are the awareness nodes. Utility nodes could be attached for DCOP cost function optimization (i.e., nodes to be grading how decision nodes favour cost functions). From figure 2, four types of sensors were used in the system. The fire has two sensors, that is, heat sensors and colour (visual sensors). Different agents are carrying these sensors, and each can raise a false detection based on the operating environment. For example, yellowish dried grass can confuse the agents using a visual sensor; agents can confirm their belief from topics broadcast by other co-agents using heat or dried material sensors and prioritise the topics of those agents during daytime (i.e., the concept of situation awareness). All agents could subscribe to the services of the agent providing wind direction in order to know the direction of the spread of the fire.

In centralized systems, agents could easily access and update their topics on time to time basis. In a decentralized approach, the agent sends request confirmation to their publishers or a medium agent (broker) to extend their messages. A variation of this approach is in (Merino et al., 2006). Cases from previous missions could be gathered and stored as text, cas, or csv file for network training using machine learning algorithms. The well-known machine learning algorithms to be used for the BBN training are expectation-maximization and gradient descent algorithms because they handle missing and uncertain data (Romanycia, 2019). The output network is a well-trained BBN for making predictions, estimation, avoiding redundant verification (request for verifying the same belief within a short time), and conclusion. It reduces the communication cost of the interaction and improves context-based reasoning and optimization. Another approach is to use the agents' self-presumption inference technique. That is, build the knowledge of the environment as if-then rules. The set of conditions are mapped to their various actions.

3 RELATED WORK

Agents' belief verification is a well-known problem in multi-agent system. Different approaches and strategies were used in solving the problem. Merino et al (Merino et al., 2006) describe a five steps (i.e., detection, alarming, confirmation, localization, and evaluation) approach for multi-agent belief verification. They used a team of heterogeneous Unmanned Aerial Vehicles (UAVs) mounted with different sensors to conduct forest fire monitoring in order to test the model. Agents raise an alarm, then other agents verify the claim. The agents will mark the area and evaluate the fire risk. They implemented a blackboard communication approach for belief verification. Yanguas-Rojas and Mojica-Nava (Yanguas-Rojas and Mojica-Nava, 2017) describe a multi-agent searching problem in which space was segmented into a set of Voronoi cells. Agents Voronoi size allocation is based on the agent's capacity (heterogeneity of the agents).

Moreover, Lumelsky and Harinarayan (Lumelsky and Harinarayan, 1997) solve the problem using the cock-tail party model. In this approach, agents navigate to other agents they want to consult and share information, a similar approach to the publish-subscribe technique. In (Gerkey and Mataric, 2002) and (Yan et al., 2011), a similar approach was used, in which agent was categorized as buyers and sellers or auctioneers and bidders, respectively. Agents will be broadcasting their knowledge and beliefs for other agents to bid (buy) based on assigned protocols.

In this paper, we propose a priority-based publish-subscribe approach for agents' belief variation handling. It uses a changing priority technique to make decisions in order to tackle the problem in dynamic environment. We also suggested Bayesian and agents' self-presumption inferential reasoning for making predictions, learning, and adaption purposes. We claim that our approach reduces communication cost (as agents can make optimal predictions without contacting other agents), can work in a dynamic environment, and improve belief authentication and agents adaptation. A potential challenge of this approach arises in belief fusion and communication failure management.

4 THE PROPOSE MODEL

Our model tackles the problem of agents' belief variation due to sensor differences using priority-based publish-subscribe, Bayesian inference, and learning technique. It uses four steps:

- Priority-base Publish-Subscribe Technique.
- Bayesian Learning
- Bayesian Inference, and
- Agents self presumption Inference

The task for the agents is to understand different knowledge, current context (situation-awareness), and topics to subscribe to in order to have genuine knowledge of the environment. Figure 1 describes the structure of generating the priority value of the topics. For example, in heterogeneous multi-agent missions for forest fire searching, during day time, agents with sensors not affected by sunlight or the nature of the scene will have higher priority such as those carrying cameras or heat sensors if the terrain has confusing scene such as dried grasses with coloured palettes like a fire. The agents with the camera will have a lower priority. The priority increase with an increase in the right decisions made and decrease with an increase in false information (false data). If agent detect a scene, it will listen to all its publisher's interesting topics, prioritize them, and make a decision by selecting the one with the highest priority. Equivalence in priority means both options are the same (have the same effect on cost function utilization). It made the approach to be adaptable for the agents. Bayesian Belief Network could be constructed (without filling in the conditional probabilities table) by a human expert e.g., using Netica (Romanycia, 2019) and put as an in-built add-in for the agents' memory. Simple if then rules will be used in monitoring the agents' behaviours during the mission. For example, if an agent detects a fire, it will update its BBN to take the effect. This allow an autonomous approach for filling in the BBN conditional probability tables during the learning process. Bayesian learning could be used in obtaining a well-trained network for making predictions, estimations, and conclusions in the absence of reliable topics or communication. That is, if agents have no updated topics from their publishers, that will be used to verify their beliefs, they can use the network for predictions, estimations, and decision-making purposes. We conducted and experiments using wildfire monitoring to monitor agents data on simulation platform. From the results, we claimed that the network prediction accuracy grows up with the increase in training data for both expectation-maximization and conjugate gradient descent algorithms used, as shown in figure 3, though we are still working on understanding the nature of the growth of the prediction error perfection and data utilization.

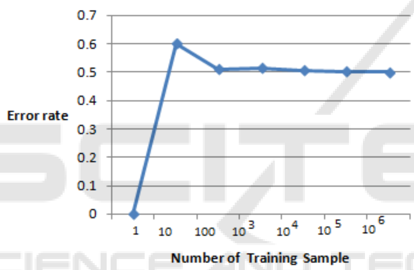

Figure 3: Prediction error rate reduces by the number of samples.

Figure 3 describes the network training perfection using 1, 10, 100, 1000, 10000, 100000, and 1000000 number of samples (mission data). From figure 3, using 1 sample data, the network gives prediction perfection fully (therefore should not be used). The prediction error rate is the number of samples predicted wrong (Romanycia, 2019).

Bayesian inference: agents could use the network to predict less important matter or in the case where communication within the system is limited, or no updated topics. We claimed that for a static environment mission, the network could make good predictions that are as nice as received information from the publisher (from our Aerospace Multi-agent Simulation Environment results and netica). In the case of a dynamic system, the agents use the time-base learning algorithm such a context-based gradient descent algorithm (Bottou, 2010; Romanycia, 2019). It considers recent cases with higher priority, as such made it to handle environment dynamism.

Agents' self presumption inference is the learned or in-built set of knowledge (in form of if-then rules) for agents' reference and decision making. In order word it is a tuple P:

$$P = \{A, C, \beta, \alpha\} \quad (1)$$

Where A is the set of agents, C is the set of conditions or logical proportions, β is the function for mapping conditions to actions, and α is the corresponding actions. Agents update their self presumption on time bases and learned new rules based on the environmental interaction and sensor data. Therefore, the agents' option starts from topic information, inferred value, and agents' self presumption. Human expert and sensor information will be responsible for updating the rules of the system.

5 CONCLUSIONS AND FUTURE WORK

We propose a multi-agent belief variation handling architecture using four main steps, priority-based publish-subscribe, Bayesian learning, Bayesian inference, and agents' self-presumption inference based on in-built or learned parameter. We claimed that (from our experiment) this approach reduces the communication cost, system failure, and improve adaptability based on environmental changes. Because the learned network could be used to make an optimal predictions, estimations, and conclusions on current and future events during the agents mission. This could remove too much communication and computation process in other call-and-confirm approaches such as in (Gerkey and Mataric, 2002; Merino et al., 2010; Merino et al., 2006; Yan et al., 2011) etc. The learning process also handles environment dynamism by prioritising recent cases in learning process over older cases and instant update of the BBN policies.

Future work focused on investigating the optimal number of samples for BBN training and nature of growing of the prediction accuracy of the learned network. Information fusion management also remain a challenge for our proposed architecture which is to be solved later. Other challenges are incomplete information due to communication failure or insufficient resources, communication protocol managements, etc.

We are also intended to innovate a way of solving redundant belief verification. That is, agents to avoid double belief authentication and deadlock occurrence solution more especially in a dynamic and uncertain situation. Finally, we will look at the effective technique for making decision more especially in a dynamic and uncertain situation. This aspect refers to effective application of game theory in agents belief verification.

ACKNOWLEDGEMENTS

We appreciate any comments that help in making this paper a great one. Our thanks also goes to Petroleum Technology Development Fund (PTDF) of Nigeria for sponsoring this project.

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