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Multi-Agent Searching Adaptation Using Levy Flight and Inferential Reasoning

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Abstract**—**In this paper, we describe how to achieve knowledge understanding and prediction (Situation Awareness (SA)) for multiple-agents conducting searching activity using Bayesian inferential reasoning and learning. Bayesian Belief Network was used to monitor agents' knowledge about their environment, and cases are recorded for the network training using expectation-maximisation or gradient descent algorithm. The well trained network will be used for decision making and environmental situation prediction. Forest fire searching by multiple UAVs was the use case. UAVs are tasked to explore a forest and find a fire for urgent actions by the fire wardens. The paper focused on two problems: (i) effective agents' path planning strategy and (ii) knowledge understanding and prediction (SA). The path planning problem by inspiring animal mode of foraging using Lévy distribution augmented with Bayesian reasoning was fully described in this paper. Results proof that the Lévy flight strategy performs better than the previous fixed-pattern (e.g., parallel sweeps) approaches in terms of energy and time utilisation. We also introduced a waypoint assessment strategy called k-previous waypoints assessment. It improves the performance of the ordinary levy flight by saving agent's resources and mission time through redundant search avoidance. The agents (UAVs) are to report their mission knowledge at the central server for interpretation and prediction purposes. Bayesian reasoning and learning were used for the SA and results proof effectiveness in different environments scenario in terms of prediction and effective knowledge representation. The prediction accuracy was measured using learning error rate, logarithm loss, and Brier score and the result proves that little agents mission that can be used for prediction within the same or different environment. Finally, we described a situation-based knowledge visualization and prediction technique for heterogeneous multi-UAV mission. While this paper proves linkage of Bayesian reasoning and learning with SA and effective searching strategy, future works is focusing on simplifying the architecture.

Keywords**—**Lèvy flight, situation awareness, multi-agent system, multi-robot coordination, autonomous system, swarm intelligence.

I. Introduction

MULTI-AGENT searching activity remains an issue in many areas such as forest fire lookouts, agents localisation, rescue missions, and surveillance, etc. The agents are tasked to find a target spread in the searching space with unknown destinations. The coordination algorithm for the agents' mission has to use their resources (energy, time, communication link, etc.) effectively, as well as support mutual behaviours among the agents. Coordination architecture can be a centralised or decentralised approach [1]-[3]. In the centralised system, the task for path planning, collision avoidance, formation control, and cooperativeness are to be controlled by the server [4]. It guaranteed optimal solutions to the coordination problem, although the outcome is not robust, needs much communication, memory, and puts more task on the controlling server [4], [5]. In a decentralised approach, agents use their sensor data (i.e., no central server) to coordinate themselves and perform the assigned task. It gives a more scalable solution, although an optimal solution may not be guaranteed [5], [6]. This paper used the decentralised approach of which agents generate their paths independently and report the mission back to the central stations.

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Different algorithms and searching patterns were developed for multi-agent searching task. These can be categorised into fixed-patterns and random approaches. In fix-pattern techniques, the agents followed a well-defined path during the mission, such as parallel track (Fig. 1), sector search, expanding square, Zamboni search, etc. [7]-[9]. This feature made them non-robust, non-scalable, and applicable only in a well-known area. Random searching approaches generated waypoint with equal chances within the space by following some probability distribution. The two well-known approaches are Lèvy flight and Brownian motion, (1) [10]-[13]. They are more scalable, robust, and applicable to an unknown environment.

$$P(\lambda) = \frac{1}{\pi}\int_0^\infty \cos(\lambda t).e^{-t\lambda^c} \quad 0<c\leq 2 \tag{1}$$

where, c is the constant, which ranges from 0 to 2. If c = 2, the distribution turns to Brownian motion and uses a Gaussian distribution. λ is the step size, and t is the time between two successive step sizes. The step size is given by (2):

$$\lambda = \frac{U}{V^{\frac{1}{c}}} \tag{2}$$

where u and v come from a uniform random number generator such as the linear congruence approach of [14].

Fig. 1 shows an example of fix-pattern searching (parallel sweeps path-planning). It describes agents performing the searching task using a parallel track [16] in one of our experiments. Agents segment the area and perform horizontal sweeps of fixed size within the searching space in order to detect the targets (yellow polygons). Rates of turning are high, and as such, consume lots of energy, although it can guarantee full coverage. Other examples of fix-pattern approaches are sector search, expanding square search, Zamboni search, and creep lining [16], [17], [22], [23]. This paper uses Lévy flight and proves its diversity and agents' resources utilisation.

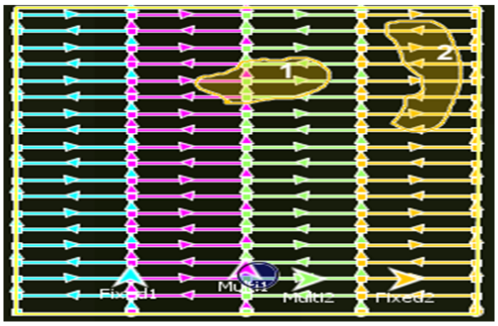

Fig. 1 Example of Fixed-pattern Searching (Parallel Track Search)

The second challenge to be addressed in this paper is the issue of knowledge understanding and prediction. That is, after agents dropped their knowledge at the central server, how can it be viewed, analysed, filtered, and make it predictable.

In this paper, we applied the Lévy flight approach for agents' path planning during search activity and proved its performance over the fixed-patterns strategies. Secondly, we proved that Bayesian reasoning and learning could be used for agents' knowledge representation, learning, and predictions for SA. The learning and prediction proved applicability for inter-environment (different environments) missions.

II. Background

A. Path Planning Using Lèvy Flight

The effectiveness of agents' missions depends on the path planning used for the mission. Therefore, the path planning needs to be very effective to utilise agents' resources (energy, mission time, etc.), so that it will be applicable to poor UAVs. Different strategies were proposed to solve multi-agent path planning for search activity problem including the grid strategies [15], [16], fixed-pattern strategies [7], [9], and nature-inspired approach [13]. Lèvy flight is the most popular example of the nature-inspired strategy in which agents make arbitrary random jumps generated using (2). It gives a well-diverse waypoint for space exploration with rare chances for repetitive search [13]. Algorithm 1 describes a way of generating waypoints using Lèvy flight for multi-agent searching activity.

Algorithm 1. Multi-agent Searching using Lèvy Flight.

1. Start
2. Generate waypoint using equations 1 and 2.
3. While a target is not found and the recent waypoint was visited.
4. Go to 2. Otherwise, go to 5
5. Stop

Algorithm 1 describes the continual waypoints generation process by the agents using ordinary Lévy flight. This approach can be improved to monitor agents resources by a terminology we called k-previous waypoints assessment. It means that the agents will be assessing their k-previous waypoints against redundancy (i.e., ensure total avoidance of repetitive search). Algorithm 1 can be changed to use k-previous assessment strategy as described in algorithm 2.

Algorithm 2. Lèvy Flight Augmented with K-previous Waypoints Assessment

1. Start
2. Generate waypoint using equations 1 and 2.
3. Communicate waypoint value with other agents
4. If it is not a redundant waypoint (i.e., it pass the sensing range) got to 5 otherwise go to 2
5. While a target is not found and the recent waypoint was visited.
6. Go to 2. Otherwise, go to 5
7. Stop

This paper applied the Lévy flight searching strategy to the multi-UAV mission for forest fire searching, as described in Fig. 1. Performance comparison was made between Lévy flight and parallel track against agents' energy and mission time utilisation.

B. SA Using Bayesian Inferential Reasoning

Bayesian inference uses conditional probability rule to make predictions on occurring events [17], [18]. Usually, the events are presented in a graphical approach known as the Bayesian Belief Network (BBN). BBN is a powerful tool that represents events in form of graphs G(V,E) where V is the events and E is a directed arrow showing a causal relationship among events. Fig. 2 describes an example of how agents represent their knowledge of the occurrence of fire.

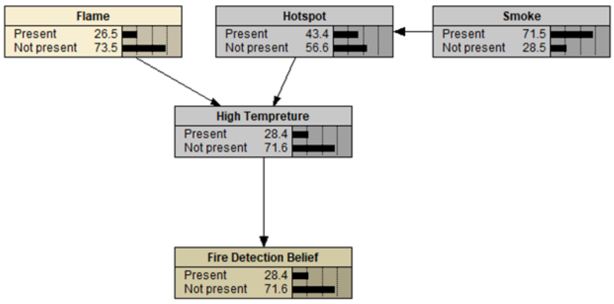

Fig. 2 Sample of BBN for Fire Detection

From Fig. 2, the BBN shows that smoke causes hotspots detection, while flame and hotspot causes high temperature. High temperature values in the node labeled "High Temperature" show fire detection. The individual agents report their missions at the base station, which has the copy of the BBN and runs a training process using gradient descent or expectation-maximisation algorithm [19], [20]. The output of the training is a well-trained BBN that is capable of doing some predictions, estimations, and uncertain information removal. This paper monitors the learning process prediction accuracy and knowledge representation for multiple heterogeneous UAVs using Bayesian reasoning and learning to produce a platform for effective knowledge understanding and prediction (SA).

III. Related Work

Multi-agent searching is a well-known problem in areas such as the rescue mission, surveillance mission, forest fire monitoring and so on. It started from the use of wardens on horses and foot, trees and tower climbing, fixed cameras, helicopters, satellite images, and more recently the unmanned aerial vehicles (UAVs). Unfortunately, UAVs have poor battery capacity which subjects all their actions to utilise its energy. Different strategies were proposed for the agents (UAVs in our case) path planning which can be generally categorised as the fixed-pattern, grid and nature-inspired approaches.

In the grid approaches, the searching space is segmented into grids with initial equal probabilities. The probability value of the grids is decremented by the number of agents' visits—agent's select grids based on high probabilistic values. In [16], agents exchange information and probabilistic values of the visited cells in order to optimise the searching strategy. This strategy needs lots of memory and wants agents to exchange messages for an effective searching strategy [21], which has serious negative effects on agents' energy.

In the fixed-pattern approach, agents follow particular patterns (e.g., the parallel sweeps in Fig. 1). This approach guarantees full space coverage but needs lots of energy, and target detection is not necessarily more especially when the environment is changing. The work [16] describes a search and rescue mission by a team of agents using parallel sweeps on the searching space (Fig. 1). Agents often change the searching strategy based on the space and probabilistic survival value. Other augmented approaches resembling parallel track search pattern are creep lining, expanding the square search, sector search, and Zamboni search of [7]-[9].

Naturally inspired mode of foraging, shelter search, and mates searching of animals were used in multi-agent environment searching [13]. The most populous approaches are Lèvy flight and Brownian motion [12], [13], which are categorised as the random space exploration techniques. Lèvy flight is more diverse, having a low chance of exploring the same place and escape from local minima [13]. It was augmented for optimisations purposes in many approaches. For instance, [13] enhances the regular Lèvy flight by integrating it with the artificial potential field. That is, agents that are close to the target will be attracting other agents toward the target while those apart will be pushing them farther. This approach ensures energy utilisation though a large sensor or communication power is needed. Reference [11] describes an extension of Lèvy jumps by selecting the best-known location as the seeds for controlling future jumps. References [12], [22] use a similar approach by inspiring the bat's sensing and flocking natural behaviours similar to an artificial potential field. A similar strategy was used in [23] inspired by insects behaviours to light (i.e., attractions).

The grid and fixed-pattern approaches have issues in a highly stochastic, dynamic, and uncertain environment. That is in a case whereby the dependent variables in making decisions are highly stochastic and have much uncertainty in their predictions. A clear example of such cases is wildfire searching, military missions, aviation, etc., [29], [30]. They are also incapable of handling heterogeneous agents' task specifications and deep context reasoning. Our approaches applied the Lèvy flight searching using a team of heterogeneous agents modelled in highly dynamic and uncertain environments and monitor the agents' energy and searching time utilisation. The agents' mission data are collected at the base station and process for understanding and prediction (i.e., SA). Unlike the SA for communication assurance, human-in-the-loop, task segmentation in [26]-[29], our approach focus attention on prediction perfection using Bayesian reasoning and learning together with situational-based knowledge visualisation for heterogeneous (different sensors) multi-UAV missions.

IV. Experimental Results

We model a forest with fires inside and tasked four UAVs, of two different types and sensors (multi-rotor-heat sensors and fixed-wing-camera sensors) to search for the fires (yellow polygons), as described in Fig. 5, using Aerospace Multi-agent Simulation Environment (AMASE) [30]. Figs. 4 (a) and (b) show the energy and time performance of Lévy flight versus the parallel track. Again, the use of algorithm 2 improved the energy and mission time utilization than the ordinary Lévy flight as described in Figs. 4 (c) and (d), although memory and communication are needed to implement that approach.

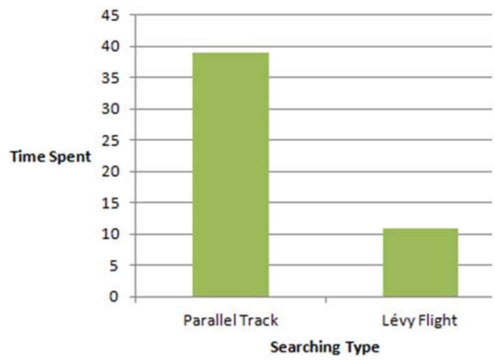

Fig. 4 (a) Agents' Energy Used Performance Comparison for Target Detections

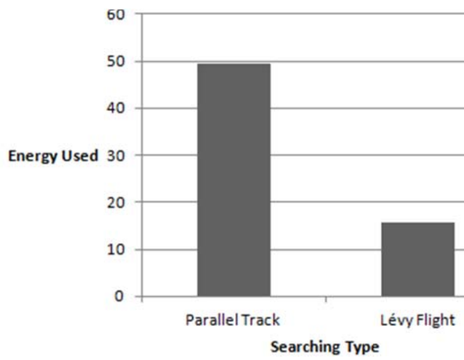

Fig. 4 (b) Agents' Mission Time Used Performance Comparison for Targets Detections

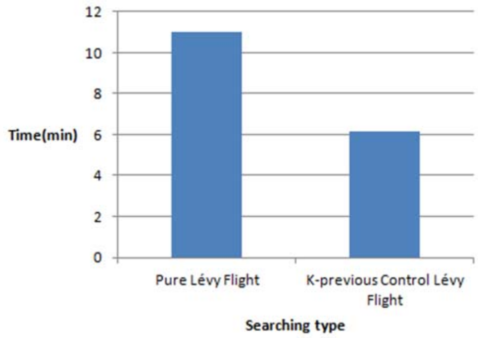

Fig. 4 (c) Agents' Mission Time Used Performance Comparison between Lévy flight and Lévy flight with K-previous Waypoints assessment

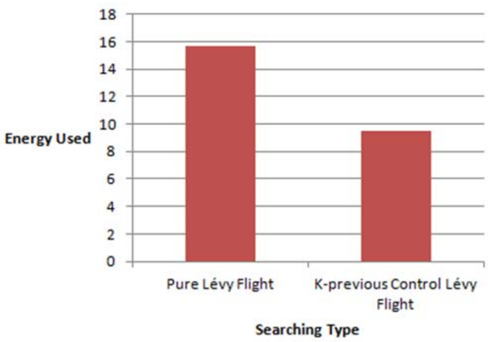

Fig. 4 (d) Agents' Mission Energy Used Performance Comparison between Lévy flight and Lévy flight with K-previous Waypoints assessment

Fig. 5 Modelled Forest, Fire, and UAVs on our AMASE platform

Figs. 4 (a) and (b) proved that the Lévy flight approach consumes less energy and mission time to explore the environment in Fig. 5, also augmenting the levy flight searching with redundancy control rules enhances the search by avoiding repetitive search. This approach uses little amount of agents' energy and time, although memory and communication are needed in order to avoid inter/intra agents redundant waypoints. After agents finished their mission, they will drop their knowledge at the base station for processing. BBN was used for the agents' knowledge representation, as described in Fig. 6. The recorded data can be used to train the BBN to be able to make predictions and estimations of uncertain events values. The trained network was used to grade future data prediction accuracy. Fig. 7 describes the result.

From Fig. 5, the rectangular yellow boundary represents the searching space, the yellow polygons are the fires, while the UAVs are the triangular shapes labelled and coloured differently. The task for the agents is to search for the fire using the least time and energy. All agents' sensor information is recorded in the events records form and train the BBN in Fig. 4 using expectation-maximisation [20] or gradient descent [19] learning algorithms (performance was the same). The expectation-maximisation algorithm finds optimal prediction by using Bayes rule to compute the prediction of missing data and then join the computed value and real data to get optimal likelihood. Gradient descent algorithm sets of an objective function and minimises it using negative log-likelihoods. We monitor the wind speed node and track the error rate, logarithm loss, and quadratic loss against the total number of samples (Figs. 7 (a)-(c)). The error rate is the average time the network fails in its prediction [31]. It ranges from 0 to 1, with 0 being the best. Logarithm loss is the difference between the overall mean of questions of all cases supplied to the network and the natural logarithm of the correct predictions (3). It ranges from 0 to infinity, where 0 is the best.

$$\text{Logarithm loss} = \sum_i^n \frac{x_i}{n} - \log y \tag{3}$$

where x_i is the set of the sample provided for training, and y is the correct prediction. Quadratic loss (Brier score) of [31] measures the probability prediction accuracy using the proper function of [31]. The Quadratic loss is given by (4):

$$\text{Quadratic loss} = \sum_i^n \frac{x_i}{n}\, 1 - 2 * y + \sum_j^n y_j^2 \tag{4}$$

where j is the number of states, Brier score ranges from 0 to 2, with 0 being the best.

Our experiment generated cases from agents in the scene of Fig. 6. Then we monitor the error rate, logarithm loss, and Brier score of one node (wind speed to keep the paper short) of the network in Fig. 6. Figs. 7 (a)-(c) show the predictions' error metrics versus the number of samples.

To test the agents' and BBN adaptability, we change the environment with different targets' position, wind speed, wind direction, etc. (see Fig. 8), and use the learned network (of Fig. 6 with 3 k cases as it is around the mean value) to test its perfection. We then monitor the error rates and display the results in Fig. 9 (a)-(c).

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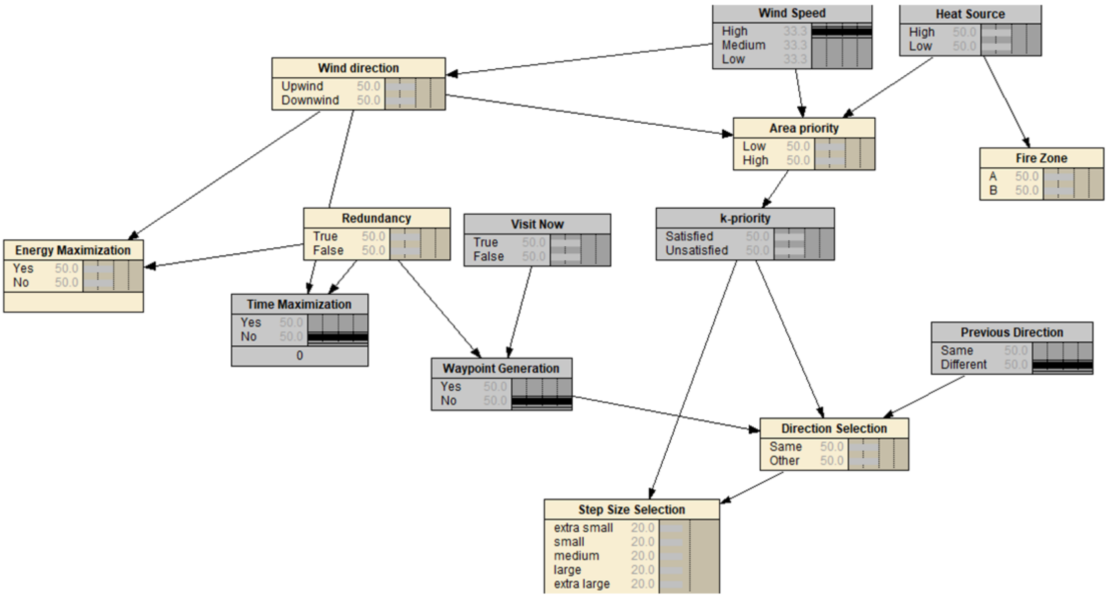

Fig. 6 BBN for Forest Fire Lookouts

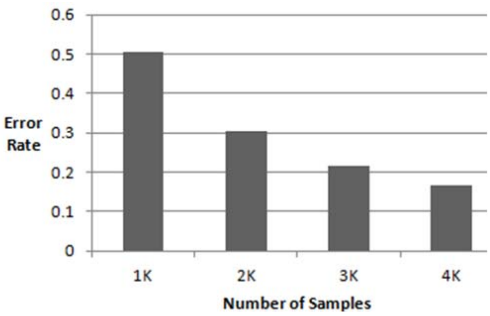

Fig. 7 (a) Error Rate versus Number of Samples (Cases)

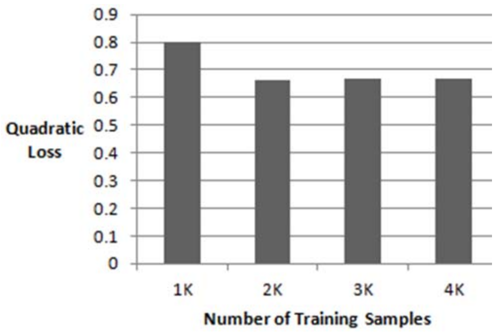

Fig. 7 (c) Quadratic Loss versus. Number of Samples (Cases)

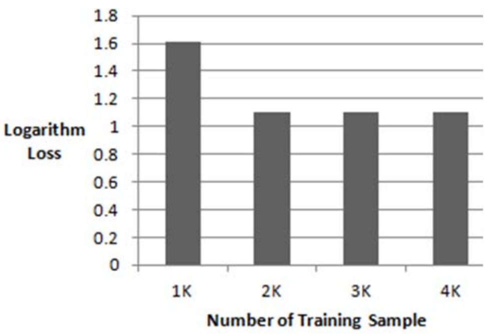

Fig. 7 (b) Logarithm Loss versus. Number of Samples (Cases)

Fig. 8 Scene to Test the BBN and agents' adaptability

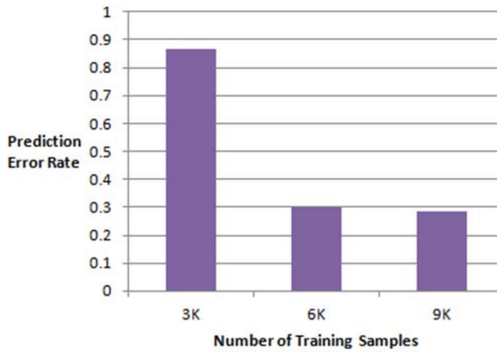

Fig. 9 (a) Error Rate versus. Number of Samples (Cases)

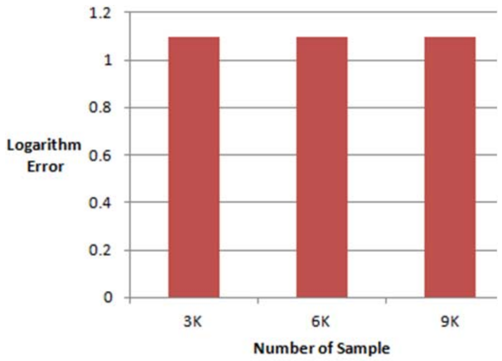

Fig. 9 (b) Logarithm Loss versus. Number of Samples (Cases)

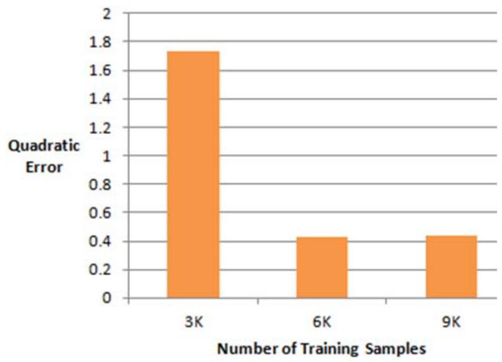

Fig. 9 (c) Quadratic Loss versus. Number of Samples (Cases)

Finally, we use the concept of the heatmap to view the agents' knowledge at the base station. The map segments the environment into grids which are to be coloured by using two colours to shows fire and no fire. Considering the fact that agents have different sensor profiles, data are ranked based on the situation of the environment using priority value. For example, the agent using a camera sensor may have low priority value during the day because it can be confused by dried grass and raise false alarm. In order to differentiate the knowledge, the same colour with different brightness is used as described in Fig. 10. This is a continuation of our work on priority-based conflict resolution in heterogeneous multi-agent mission in [32].

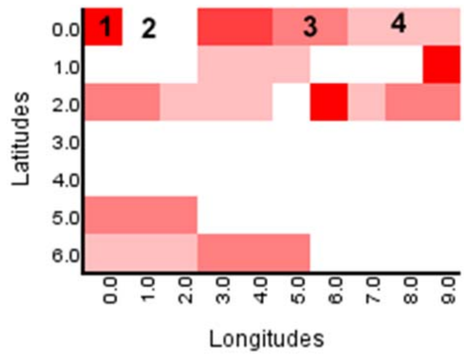

Fig. 10 Situational-based Knowledge Representation

Fig. 10 describes a colour-based knowledge representation for heterogeneous. The white colour represents 'no fire' and the different version of red colours (labelled 1, 3, and 4) signify fire present based on their priority i.e., 1 is more confirm than 2, and 2 is more confirm than 3, and 3 is more confirm than 4..

V. Discussion

Figs. 4 (a) and (b) describe the efficiency of Lévy flight approach over the parallel track approach, which minimised the energy and searching time of the agents. This occurs as a result of its production of well-spread waypoints. Less energy and mission time can be used when the ordinary Lévy flight was augmented with the k-previous waypoint assessment strategy as describe in Figs. 4 (c) and (d).

From Fig. 7 (a), the BBN and the agents' predictions accuracy and adaptability are directly proportional to the number of training data for the learning algorithm. The difference in learning accuracy becomes very small when the agent experiences most of the environmental cases. This signifies the sufficiency of training data at that steady-state level (mean value of the training set), and a higher sample may cause the network to be worse again. This feature also exists in logarithm loss and the Brier score in Figs. 7 (b) and (c), but they are more stable than the error rates.

Fig. 6 describes the change in the environment, and the network learned with 3k (3000 number of samples in Fig. 7, as it is around the mean value of the trained data normal distribution) was used to test the accuracy of the cases in Fig. 6. Figs. 9 (a)-(c) display the results of the test with 3000, 6000, and 9000 numbers of samples. Still, the adaptability, prediction accuracy, logarithm, and Brier Score are directly proportional to the number of samples. Similarly, as the number of data increase, the prediction accuracy differences become very small. The reason is because the network has explored most of the training data. For example, when we observe the network performance of Fig. 9 using 6000 and 9000 number of samples, of course, the difference is very small. Secondly, the difference will not be the same when agents are operating in a rapidly changing environment, because the node entries are always changing, as such the learning process needs to prioritise some entries over the others. The priority process can be achieved by setting up a degree factor for the set of variables as described in [32], [33].

The perfection of the prediction accuracy can be applied to authenticate waypoints to be visited, predicting other agents' actions and filter uncertain data. In summary, we claim that Lévy flight searching strategy performs better than parallel track, and the Bayesian inference and learning will improve agents' adaptability, SA, cognitive and collaborative behaviours, uncertainty tolerance, and context reasoning, which will reduce agents' resource consumption. For example, if agents can predict other co-agents' actions and dynamic environmental factors (wind speed, wind direction, stock exchange fluctuation) and their uncertainties using Bayesian inference and learning (as described), they are then able to optimise their sensor usage, guess other co-agents' actions and support them. Expectation-maximization (EM) and gradient descent (GD) algorithms handle uncertainties and missing data which is a crucial problem bedevilling multi-agent system [29], [34] and we tackled that with Bayesian inferential reasoning and use multi-agent searching using Lèvy flight as a use case.

VI. Conclusion

We prove that the Lévy flight performs better than the fixed-pattern (parallel sweep) in terms of energy and mission time utilisation. We also describe how multi-agent searching adaptation can be performed using Bayesian reasoning and learning. Our experiments use cases from different scenarios to test the prediction perfection, logarithm loss, and Brier score of the BBN in different environments. Experiment results show the perfection of the prediction with little training data using expectation–maximisation or gradient descent learning algorithms. The adaptation features increase the agents' reasoning and hence, reduce resource consumption. Our use of algorithms (expectation-maximisation and gradient descent algorithms) tolerates uncertain and missing data, which can be coupled to multi-agent resource utilisation. Finally, we describe a context-based agents knowledge visualization for decision making at the base station.

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