Detection of Faults in Flying Wireless Sensor Networks Using Adaptive Reinforcement Learning

G.Kiruthiga, K.Kalaiselvi, R.S Shudapreyaa, V.Dineshbabu

ABSTRACT---In recent decade, diagnosing the fault in Unmanned Autonomous Vehicle (UAV) based Wireless Sensor Networks (WSN) has received a little attention by the researchers. The limitations of UAV-WSN environment possibly affects the fault diagnosis. The limitations associated with UAV-WSN conditions are considered as the scope of present study in diagnosing the fault in network. The study focuses mainly on improving the overall lifespan of network and further it tends to increase the network scalability. Since, the overall network lifetime and scalability reduces as the condition of the network worsens. Hence, the observation on network becomes poor in identifying the faults associated with the network. To resolve the issue, anAdaptive Reinforcement Learning is proposed in the study for the fault detection of flying sensor nodes in UAV-WSN. This approach diagnoses the faults in the network in an effective way and improves the overall efficiency of the network.

KeywordsFault diagnosis, UAV, WSN, Adaptive Reinforcement learning

I. INTRODUCTION

The interest of a wide range of applications is significant for unmanned aerial vehicle (UAVs) and aerial robots[1]. In several of them, there can be significant advantages of active cooperation between various UAVs[2].Fault detection and identification technology (FDI) plays an important role in efforts to enhance system reliability in aerial vehicles.Most of the FDI and UAV applications that appear in the literature are based on model-based methods, trying to diagnose defects by redundancies of some system dynamic mathematical description.For non-manned aircraft, FDI was applied either with a UAV wing or a UAV helicopter.

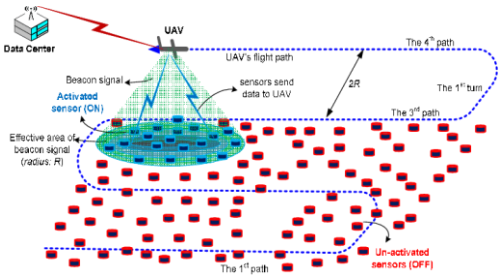

Figure 1: UAV- WSN Architecutre

Differential GPS Receivers (DGPS) can achieve accuracy in positioning UAV main sensors. Because they generally are the only absolute position sensors in UAVs, their measurement reliability is critical for UAV missions.When DGPS readings are incorrect or when the variable modes are lost it may cause large drift errors in position estimation.

There is an extensive detection in the literature concerning the fault detection [6]- [13], in finding the incorrect measurement which is said to be the Receiver Autonomous Integrity Monitoring [3]. It has different techniques in developing the faut.

The common objects can be identified at the place using a variety of UAVs when a visual camera is eqiuipped with it. For example, the matching of the obtained same landmarks with two UAV's and identifying the landmarks[2] which is natural by using a robust technique. it shows the displacement among both the UAVs in relative pose. This fault can be detected, for example, if the DGPS of UAV-A is defective, by using UAV-B's DGPS and the relative image position estimates. The proposal is to estimate UAV-A's position using the known UAVB position and the relative UAV-A and UAV-B position estimates using the method outlined above.Unfortunately, the accuracy and noise levels of these vision-based position estimates vary from different factors.

This paper therefore adopts a variable threshold Strategy using Adaptive Reinforcement Learningto detect a fault. Moreover, the likelihood of a similar scene in the field of view of two or more UAVs is not very high when carrying out a plan in multi-UAV missions.

II. FAULT DETECTION IN UAV-WSN USING ADAPTIVE REINFORCEMENT LEARNING

In current research, its reinforcement learning module is the agent for the intelligent block problem, which tries to find the failures along the entire flight path. The adaptive enhancement learning model consists of two main components.

Consider the overall situation of an agent interacting with an environment shown in Figure 2. At every stage *t*, the agent observes a certain state st and needs to select a measure. The environmental state changes to s_t+1 and the agent received the reward rt following the action. State transitions and rewards are stochastic and are supposed to be

Revised Manuscript Received on June 10, 2019.

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properties of Markov i.e. the probability of a state transition and the rewards only depends on the environmental status st and the action of the agent a_t.

The first element is that agents learn value that matches a set of strategy, not values that match individual strategies as they did in previous publications [4].Especially the set of all strategies is divided into tiles, which mean a partition tileInstead, any strategy from the tile will lead to the reinforcing of the tile. The agent will therefore estimate the value of playing a specific strategy based on the value of the tile in which it is found.

In the second element, the partition changes over time. The second part. In particular, we are building on a recent approach method known as tile adaptation [5]. The method begins with a coarse partition containing just one tile.The partition is improved with the time as the agent knows. While and where to improve the partition is the key issues in the process of refinement. The wide answers are: when the learning of this score has converged and refined to maximize the improved value function, this score will be further refined. By adding a sensitivity parameter to increase the algorithm, the partition becomes more accurate

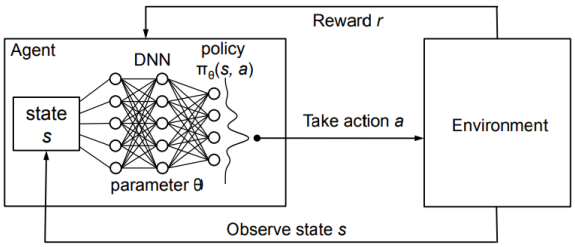

Figure 1: Architecture of Reinforcement learning

When selecting the next action in its current state, the Reinforcement Learning Agent always faces a dilemma of exploration and exploitation. When it chooses a gullible action which takes the current state of the highest priority, it exploits its previously gained knowledge of the values of the action. Instead of selecting one of the non-graceful actions, it explores the value of the non-graceful actions.The reinforcement student uses a common probability policy at the early stage of the learning, according to which every action has the same probability of being taken. It can explore as many states and actions as possible in this way. It changes at the middle stage to the Gibbs Softmax policy, under which higher preferred actions are more likely to be chosen.The module can partially explore and partially exploit simultaneously by using this policy. It uses a greedy policy in the final stage that enables it to make full use of its experience before.

The key issue is the choice of action by means of a vector value. In this case, $Q(s,a)$ is not a basic value, because it is a vector value, and for the first and second object the action is considered maximal and ideal. Multiple non- dominated actions are represented as the relationship of Pareto-dominance. The agent is used in defining the order of the vector value with an action selection function that permits required action in Eq.(1).

The action selection function (U) is used to find the fault and non-fault nodes,

$$U\big(Q(s,a),Q(s,b)\big)=\begin{cases}+1 & \text{if } Q(s,a)\succ Q(s,b)\\ -1 & \text{if } Q(s,a)\prec Q(s,b)\\ 0 & otherwise\, Q(s,a)\sim Q(s,b)\end{cases} \quad \textbf{(1)}$$

The scalarisation function (f) is implemented over action selection function (U) to map the values of vector to the values of vector, which is given by,

$$U_{scalar}\big(Q(s,a),Q(s,b)\big)=\begin{cases}+1 & \text{if } f\big(Q(s,a)\big)>f\big(Q(s,b)\big)\\ -1 & \text{if } f\big(Q(s,a)\big)<f\big(Q(s,b)\big)\\ 0 & otherwise\ f\big(Q(s,a)\big)=f\big(Q(s,b)\big)\end{cases} \quad \textbf{(2)}$$

Hence, to maintain trade-off between the objective function i.e. fault nodes.

The scalarisation is estimated as linear weighted sum of cost and path as in Eq.(3) with weights w_o provides the importance of the following objective function:

$$f\big(Q(s,a)\big)=\sum_{o=1}^{n} w_o Q(s,a,o) \quad \textbf{(3)}$$

As it is difficult to calculate the concept of reward for action (finding the faults), linear scaling is added since simple transactions are performed.

III. PERFORMANCE EVALUATION & RESULTS

Figure 3 illustrates an accumulated fault detection production function (CDF), for custom techniques of training while the Phasor Measurement Unit interaction delay interval is[10,80] and[10,180] ms, respectively, in each case (9000 test cases for each curve)[10,80] ms. The time of detection is defined as the length between the failure occurrence and the fault sensors.In 90% of all cases, when the defect detector is trained in view of the delayed arrival of measurements, we read that, compared to only 20% of cases in less than 20 ms detected in training of synchronized measurements, the defective condition is detected in less than 20 ms.

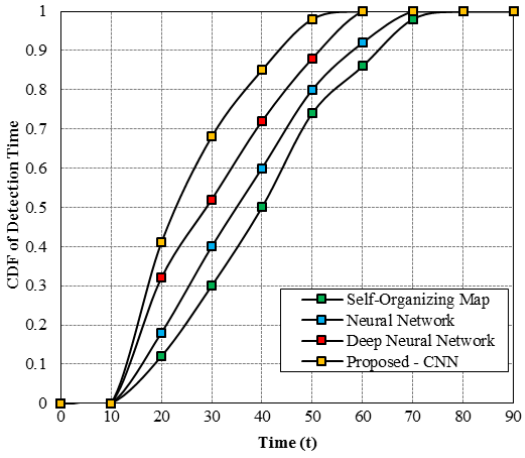

Figure 3: CDF of detection time for finding the faults over 9000 test cases having delays between 10 and 80 ms

IV. CONCLUSIONS

In autonomous UAV navigation, default detection is an important issue. In particular, the catastrophic effects of GPS transient failures that are very common in some scenarios. In the event of gps failures, computer vision may be used to estimate relative positions. In this paper, the use of Adaptive Reinforcement learning to increase reliability in multi-UAV systems has been shown by machine learning techniques. In the future work will include the use of cameras on locations or transferred by people and other sensors, the proposed method will be verified experimentally using the data generated by experiments in field UAV monitoring.

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