Original Article

Development Of Coordinates Based Cnnshortestpath Algorithm For The Prediction Of The Uav Travel Path Based On The Drone Node Dataset – An Alpha Defensive Path Prediction

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Abstract

Today is the era of ultra-age technology and practices for the betterment of the society. Drone is the Unmanned Aerial Vehicle (UAV), which needs a path planning to reach up to the target. There are two basic modes for use of drone in case of military/surveillance: first is attack mode and defensive mode. Hence, this paper focuses on defensive mode as a scope of the proposed study. This paper provides significance of drone surveillance, a new artificial intelligence strategy to develop a predictive model based on the path planning. Further, based on the drone dataset, the UAV travel graph can be predicted and tested with a recursive machine learning algorithm. This strategy can be clubbed as an image path using deep learning algorithm also but to ensure the graph-based training and testing, the proposed research will use CNN algorithm for comparative analysis of simulated path's plan coordinates. This further can be developed as a human-machine interface module.

Keywords: Artificial Intelligence, Drone, UAV, Path planning, machine learning, HMI

1. INTRODUCTION

UAVs are utilized for observation as well as strategic planning. This technological know-how is nowadays obtainable for usage in the disaster response domain to help the team associates. UAV or an unmanned aerial vehicle is a remote-controlled airplane [1]. It can be controlled wirelessly in real-time and pre-programmed to fly autonomously on the pre-defined tracks. Widely referred to as a drone, the usage of this type of aircraft is raising in all segments. It is crucial to notice that missiles that fly autonomously are certainly not classified as UAVs. These kinds of attack devices are categorized independently within the weaponry categories. UAVs or drones can be grouped in numerous ways [2]. UAVs are extremely compact, which allows them to perform the job even in remote destinations where there are no physical or technical facilities. Primarily, UAVs were employed only for armed forces tasks. Even so, with their particular raising status, technical developments and popularity among the people in industry as well as research, their uses are no longer narrowed to military applications [3]. UAV system has quickly transformed topology because of excessive movement devices. Presently, Mobile adhoc networks (MANETs) routing is employed for interaction in UAV systems. The specifications for interaction system in flying adhoc Networks are yet to be designed. UAV system buffering data requires a protocol with superior bandwidth, significant flexibility, changing link constancy and large energy intake compare to adhoc networks. It directs to suddenly draining communication in between UAV-to-UAV and UAV-to-ground [4].

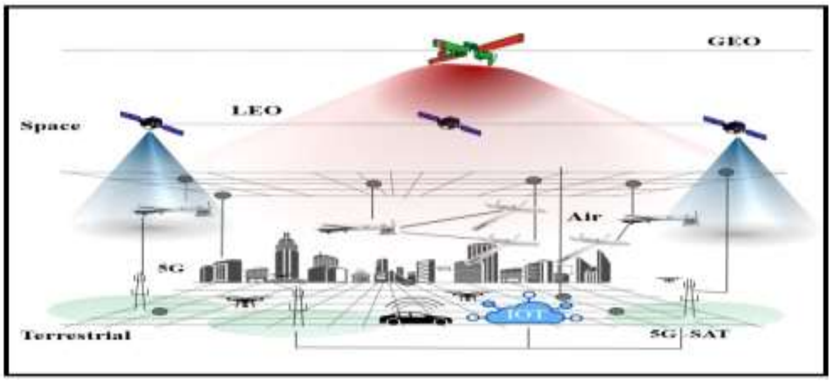

Fig. 1: UAV communication entities (Thomas Magesacher et. al., 2019)

Cellular systems are an evident option for UAV CNPC links; however, they have their disadvantages, as recently mentioned. The probable speed controlling of UAVs as well as alterations in antenna positioning may stimulate solid falling. Consequently, alterations may be needed in physical layer structure, just like changing orthogonal frequency division multiplexing (OFDM) to filter bank multi-carrier (FBMC), orthogonal chirp spread spectrum (OCSS), and several modulations [5].A major concern in armed forces functions is the capability to execute intelligence, surveillance as well as reconnaissance (ISR). ISR can be accomplished from predetermined properties including long range radars and surveillance cameras, or perhaps transport assets such as aircraft, satellites and unmanned aerial vehicles (UAVs), or a pairing of each of those. Certainly, there is a significant range of sensors allowing the transformation of sophisticated programs of systems, like sensor networks (SNs). In basic, an SN is a network of nodes that enables the monitoring of the situations by means of each node's one or perhaps more sensors.

Sensors respond to their situations by means of a range of sensors, from video cams to motion sensors to numerous radars [6]. At the time of the last decades the UAS sector has grown up considerably, primarily due to the advancement and growth of armed forces applications, accompanied by a large array of civil products, just like national boundaries control, coastguard, legislation enforcement as well as police support, terrain surveillance, geographical surveillance, communications, etc. [7]. The independent artificial intelligence UAVs were manufactured utilizing laser-range detectors for location analysis as well as path procuring with extremely accurate preciseness. Even though the UAVs float in the locality, it confirms a unique 3-D map of its encircling [8].

The relevance of urban monitoring has further more boosted multiple times in the latest times because of the expansion of grey region combat and disputes where the grey sector actors employ methods such as falsehoods, violence, and interferences of services as well as crucial infrastructures to destabilize countries and possibly create auspicious circumstances for armed forces events. Even though metropolitan surveillance as well as monitoring systems have been launched recently, many of these systems are not really able to execute in real time. Real-time metropolitan monitoring as well as monitoring is essential for boosting public protection and national surveillance, and consequently this study stresses on real time surveillance as well as monitoring [9].

2. LITERATURE REVIEW

The effect of Artificial Intelligence (AI) on the everyday life is rising. AI is swiftly evolving the aspect of the day-by-day works, affecting the ordinary way of individual thinking as well as connections with the situations. How should the unique laws be built to protect the recent and upcoming generations from the unfavorable facets of AI and improve its positive influences over mankind? Furthermore, how AI-assisted guidelines and rules need to be created to guarantee sociable and economical betterment [10]. Drones have verified their potential in offering real time, affordable alternatives for different applications as health care, smart grid surveillance, smart city monitoring, as well as national boundaries surveillance. Even though it has various surveillance and level of privacy concerns, experts around the world have given several alternatives to safeguard drone interaction from cyber-attacks. Many of such alternatives were structured on cryptographic methods and are very computationally intensive. There are few blockchain-based alternatives that undergo from large transaction backup expense of communication stability, latency, as well as bandwidth issues [11].

Various attacks against the UAV are getting common, as they are very easy to execute with cheap components, just like spoofing and jamming. Regrettably, as many of such vulnerabilities exist among base technologies, protecting the UAV becomes a complicated task. An appealing strategy for determining and decrease such attacks is the development of a smart intrusion discovery system (IDS) [12].

Furthermore, prevalent strategies, e.g., path-following process as well as synchronize descent technique, are not appropriate to resolve the issue taken into account in this study by author(s). This suggested HHO-based formula discovers alternatives for UAV's positioning as well as power allocation concurrently, whereas the coordinate descent approach requires breaking down the initial issue into sub-problems and then fix them conversely in an iterative manner [13].

Planning the trajectory path of UAVs often needs optimization algorithms to improve the trajectory path. Optimization strategies generally fall into deterministic numerical programming techniques and stochastic metaheuristic methods. Nevertheless, deterministic techniques of mathematical programming are susceptible to stagnation in non-linear space analysis, which needs high planning for arithmetic. Throughout the earlier times, stochastic metaheuristic methods have been progressively accustomed to resolve UAV path planning challenges because of their versatility, convenience, and capability to prevent local optimization [14].

The aim of path planning seeks at locating the ideal flight from the start off position to the final position. One significant characteristic of path planning is the barrier deterrence, which means the UAV has to prevent the hurdles at the time of rendering no matter they are stationary in moving. On the other hand, with the very quickly developing machine learning (ML) as well as reinforcement learning (RL) methods, the UAV path planning strategies have pointed out a new page [15]. In latest years, experts turn toward to a new type of approach called hybridization, which is a pairing of many meta-heuristic methods for optimization. In this technique, the proficient collaboration can show a more effective optimization in the event that dealing with genuine challenges [16].

Reinforcement learning (RL) allows an agent to train autonomously an optimum plan to increase total advantages using trial-and-error communications with its environment. Model-free RL solutions have become famous in the domain of path planning. The Q-learning algorithm has been extensively applied to path planning [17]. The interaction routines among heterogeneous UAVs contain different elements of UAV interaction, networking, formation, as well as path planning. The application fields that were mainly targeted on were search, rescue, monitoring, as well as surveillance tasks. The entire pattern demonstrated that interest in diverse heterogeneous UAV practices rises through time with a concentrate on UAV networks, composition, and path planning even though considering communication as an implicit part of all such structures [18].

3. RESEARCH METHODOLOGY

The UAV path planning is the base for UAV launching, travel and safe landing. However, there is a need for automated/artificial intelligence to train such surveillance UAVs, which can be done only using deep learning modules for CNN communication. The physical layer of setup is important, but data/communication layer is the core of path planning. The proposed research scenario is to identify the path and communication patterns among the maximum 8 quad-nodes. For the proposed research, we assumed quad-node sequencing (as a path coordinates) for data transfer.

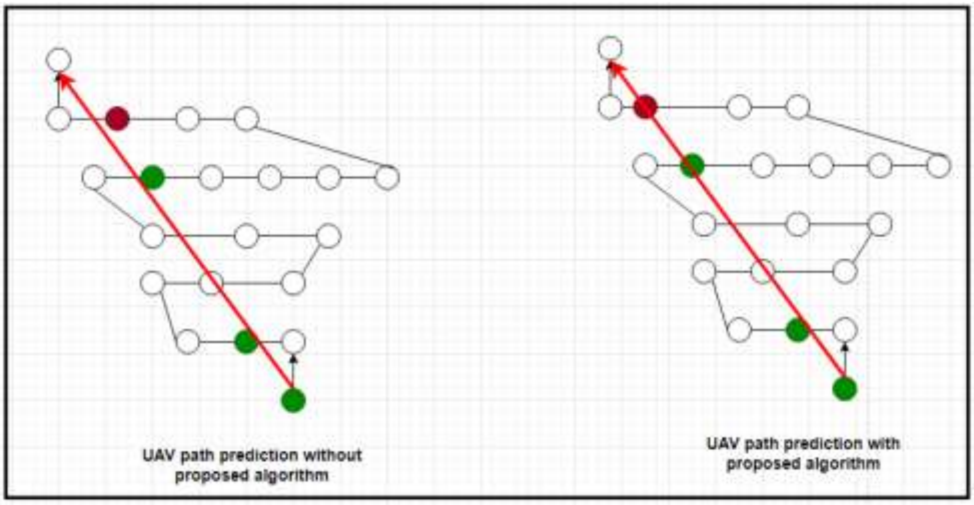

Fig. 1: Proposed Graph Based Path Planning

Fig. 1 above shows the graph-based path planning for and with the proposed algorithm. The proposed system is assumed to be a defensive system which can be applicable for drone patrolling, emergency prescribed medicine supply in war situation or any other unmanned situation requirements like chemical factory accidents, etc. In summary, assume there are ‘Qn’ quad-nodes and ‘Sn’ detector nodes. The data accumulation and serialization of request/responses are ‘Sr’ = (r1, r2,.., rn), where ‘r’ represents the request/response ID, which will be used by quad-nodes. Further, the following newly developed CNN algorithm will be executed for the shortest path to reach the target.

Proposed Algorithm: CNN Shortest Path

Input: UAV coordinatesQuad-node IDs, Target distance (Td)
Output: Shortest path plan
Given UAV_ID, territory coordinates Array T [],
for T[] = 1, T++

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if emergency sensor state == ‘Active’
then UAV_ID status == ‘Ready’ && command == ‘takeoff’
Get Target distance == Td
Get Quad-node IDs == Qid
Set UAV coordinates ()
Set inter UAV coordinates Uco[]
Get territory graph coordinates ()
Check Quad-node Sequencing ()
Calculate inline distance of target
Capture territory graph coordinates
Create coordinate dataset Cd []
Set Max_pooling ()
Set ReLu ()
Set Epoch =100
Run CNN training (Cd [])
Run CNN validation (Cd [])
Get Shortest_path()
Set Shortest_path()
End
```

4. RESULT AND DISCUSSIONS

Based on algorithmic and CNN execution with epoch size 100 for GPU execution, we identified the optimum node data distance and shortest path planning results, as shown in Table 1 and Table 2 below.

Table 1: Average total distance of UAVs with difference algorithmic performance for four quad-data nodes

No. of Data nodes	**2**	**4**	**6**	**8**
Proposed deep learning CNNShortestPath Algorithm (m)	11056	11142	14278	26235
Random forest Path Algorithm (m)	11114	12216	15405	29589
Genetic Algorithm (m)	11216	12289	16587	35741

From Table 1, it is clear that four quad data nodes perform well in the case of the proposed algorithm. The distance between different UAVs (here four UAV nodes) and each quad-node data reception is fast because the distance among UAVs is less and hence communication and data channels can transmit surveillance data quickly.

Table 2: Average UAV shortest-path finding for scheduled target for different algorithms and quad-node data reception (For testing purpose, target distance radius = 1KM)

No. of Data nodes	**2**	**4**	**6**	**8**
Proposed deep learning AI Path Algorithm (m)	891	678	547	416
Random forest Path Algorithm (m)	945	765	532	436
Genetic Algorithm (m)	942	723	549	428

The most important element in case of surveillance is to act in a quick mode and take action. In the case of UAV, it is important to reach to the target in a minimum time span. Hence, as per the proposed algorithm, path planning is based on shortest path identification and these can be stored as historical data to the cloud storage for future reference.

5. CONCLUSION

As per the objective of this paper, UAV path prediction has been done with the proposed deep learning algorithm. The performance has been tested with existing machine learning algorithms and the proposed algorithm performance is better than existing systems. The shortest path has been identified using the proposed algorithm, which is based on the graph of coordinates of drone/UAV. The proposed algorithm can be very useful for any surveillance requirement in industry and/or military applications.

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