Indonesian Journal of Electrical Engineering and Computer Science
Vol. 29, No. 2, February 2023, pp. 1192∼1200
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v29.i2.pp1192-1200

Intelligent UAV path planning framework using artificial neural network and artificial potential field

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Article Info

Article history:

Received Jul 5, 2022
Revised Oct 21, 2022
Accepted Nov 3, 2022

Keywords:

Artificial neural network
Artificial potential field
Path planning
Unmanned aerial vehicle

ABSTRACT

Unmanned aerial vehicles (UAVs) are utilized extensively in various fields of daily activities in the day to day life and industrial applications. The raises of utilization of UAVs guide the researchers to concentrate on various problems like handling rich and large-scale information and uninterrupted communication. Further, to achieve the above the obstacle free zone is mandatory and the present autonomous drones may fail to handle such situations. To address the mentioned issues, an effective path planning algorithm is needed, to find the optimal path and obstacle free mobility. Hence, UAV path planning needs intelligent and autonomous navigation system by providing high level of optimization in order to attain optimal path with the obstacles avoidance. In this paper, AI employed framework for UAV path planning is proposed by utilizing the salient features of both artificial neural network (ANN) and artificial potential field (APF). ANN is implemented for obtaining optimal path and APF is utilized for evading the obstacles throughout the path. Further, the implementation results show the better performance than the existing works in terms of the collision free optimal path for UAVs.

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1. INTRODUCTION

In current decade growth of unmanned aerial vehicles (UAV) is vast and it holds considerable amount of contribution in the worldwide economy. Application areas of UAVs concentrated in various fields related to business, utilization and governments purposes too. UAVs are also employed for industry based applications [1]. Early stage detection of forest fire can be performed by operating UAVs where green environment is saved. UAV path planning is required like these scenarios in which heights of the trees and altitude level of flight way also matters. Because UAVs utilize lower level than higher level altitude. UAV path planning ensures the safe flight way by avoiding the obstacles. They involve in various operations like rescue jobs, observing, launching missiles, safeguarding environment, communication and delivery [2], [3].

Methods implemented for UAV path planning play important role in concerning the degree of autonomy [4]. Optimal path detection is the ultimate aim of UAV path planning process with in minimum period of time by ensuring safety measures [5]. Multiple research works are carried in UAV path planning research area for obtaining optimal path without collision like A* algorithm, D* Algorithm, visibility graph, random tree, dijkstras algorithm, probabilistic roadmap and so on [6]. Optimal decision making will provide remedy for the problems related to UAV path planning. Choosing the shortest path without collision is a challengeable task for researchers. Path planning approaches are mainly classified into three types on the basis of representation, with cooperation and without cooperation depicted in Figure 1 Analysis are performed by these approaches by considering the factors like UAV coverage in the entire field and connectivity between UAVs.

In this paper, we propose a framework that ensures the obstacles avoidance by implementing artificial potential field (APF). It reduces the complexity of obstacles of the UAV path and provides end to end communication in easy manner. In addition, artificial neural network (ANN) is built for obtaining the optimal math in safe manner with minimum cost. The rest of the paper is categorized as the following sections: section 2 details the review work done regarding UAV path planning, section 3 details the importance of ANN and APF for this proposed work and in section 3 describes our proposed intelligent framework for UAV path planning, section 4 describes the implementation details and results and finally conclusion is presented in section 5.

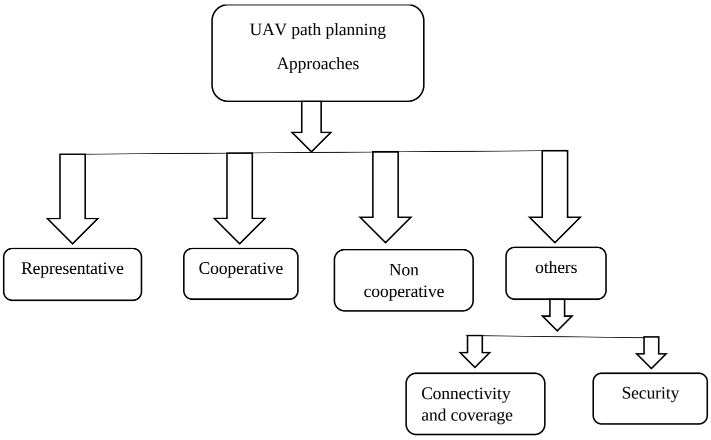

Figure 1. UAV path planning approach

2. RELATED WORK

Multiple technologies and machineries are developed for making comfortable working environment and improving outcome enormously for the decades. Researches in aerial robotics field step forward further in different industry works which is implied from the revolution of robotics. Real time model for UAV path planning is proposed by implementing genetic algorithm (GA) [7]. Path planning model of UAV is implemented by utilizing multiobjective ant colony system on the basis of Voronoi [8]. It is suitable for unspecified dynamic environment and helps for detecting nearby obstacles. Issues in the planning of three-dimensional paths for UAVs are overcome by implementing a model with the utilization of particle swarm optimization (PSO) approach [9]. It provides better quickness than GA and deals with minimum number of individual problems. Survey is carried over differential evolution (DE) variants and its usages in various kinds of issues [10]. UAV navigation planning method without collision is implemented for self-directed unmanned helicopter [11]. DE is adapted for UAV path planning which is an important approach in the process of evolutionary computing. It is utilized for the multiple dimensional related functions of the real time environment. It is mostly chosen for resolving optimization problems which are broken and similar. DE is applied for implementing UAV path planning method for attaining global optimization [12], [13]. Heuristic A* algorithm is utilized for UAV path planning [14]. Improved A* algorithm is proposed for the purpose of planning UAV to obtain enhanced rate of survival which cares about low energy consumption [15].

Growth of UAV and its usages can be found in [16]. Military surveillances and rescue processes make use of UAVs. Optimal time and path are the major issues in the process of planning paths of UAVs. In addition, safety measurements need to be considered while performing navigation. Glow-worm swarm optimization method is implemented in order to provide optimal path for UAV without collision [17]. It is utilized for operating UAV model with huge size environment. Lyapunov guidance vector field (LGVF) is utilized for implementing a method for UAV path planning by providing enhanced flight height [18]. Grey wolf optimization is employed for obtaining path with high optimization in anonymous environment with dynamicity [19].

While considering heuristic based classical algorithms, recent novel algorithms based on the inspiration of nature provide better results for the path planning process of UAVs. Brain storming optimization (BSO) algorithm is one of example for such that case which is established first in the year 2011 [20], [21]. Problems in getting optimal paths are resolved by employing this algorithm. Loopholes of BSO algorithm are overcome by performing modifications in 3 distinct aspects of approaches such as clustering, creating and selecting [22], [23]. PSO is accompanied with global best guidance concept for improving the performance of UAV path planning [24]. While comparing the implementation results, global-best BSO (GBSO) provides improved level of performance than BSO in the same environment. Though metaheuristic-based approaches are providing better results in the field of UAV path planning still there are not satisfying the necessities in the real time environment where unexpected obstacles and threats affect the system. To resolve this issue re planning of local paths is mandatory over the complicated and unexpected threat environment.

3. PROPOSED FRAMEWORK

3.1. Artificial neural network

In this work, artificial neural network is utilized for training the data [25]. ANN is divided into three layers which are input, hidden and output layers. To achieve better performance, it is possible for applying both forward and backward propagations. Set of rules for learning are set by back propagation to lead ANN. Input layer removes the unwanted data from the pooled data on the basis of filtering irrelevant data. Training parameters are defined in this stage which will be more useful for initializing path planning process and optimal path detection. Multiple operations are performed by hidden layers. In training part patterns are obtained from the data given. Outcome produced from the data is checked with the desired outcome while implementing supervised learning technique. ANN is utilized for proposing this intelligent framework for UAV path planning because of its salient features of learning and training. Basic architecture of ANN is given in the Figure 2. It is built with the combination of 4 components. Input, weight of the connection, transfer function and output are those four components [26]. Defines the input of ANN. Inputs multiplied are known as connection weight denoted w_n. Transfer x_n function computes the results. ANN is implemented on the basis of radial basis function (RBF) which is utilized as activation function. Outcome of the network would be the precise blending of both RBF of inputs and parameters related to neurons. Usually a RBF has multiple applications like approximating functions, predicting time series, classification and controlling system.

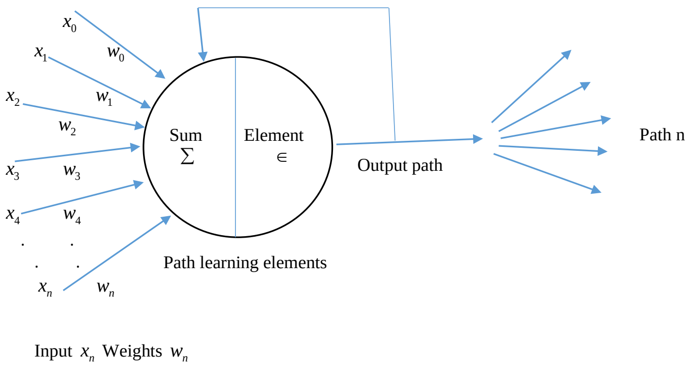

Figure 2. Basic artificial neural network

RBF based ANN consists of three layers which are input, hidden and a layer with the combination of nonlinear RBF and linear output. Input modeling is done as a trajectory of real numeral values i.e. $x \in \mathbb{R}^n$ further it is derived as (1).

$$\varphi(x) = \sum_{i=1}^{N} a_i \rho(||X - c_i||) \tag{1}$$

Here, N represents the amount of neurons of the hidden layer, c_i represents center vector of neuron i and a_i represents the weight of i. Radial basis function is defined by implementing of dependency of functions over distance from c_i. Each and every input is connected to neuron of hidden layer respectively. It is derived by incorporating Euclidean distance for enhancing pattern recognition. Further, Gaussian is implied for radial basis function.

$$\rho(||x - c_i||) = \exp[-\beta||x - c_i||^2] \quad (2)$$

Here, Gaussian basis functions considered as local to ci which derives as (3).

$$\lim_{||x||\to\infty} \rho(||x - c_i||) = 0 \quad (3)$$

In that above case alternating parameters of one neuron will not affect the model of the network. RBF based artificial neural networks acts as global approximators over the subset of $\mathbb{R}^n$. Parameters such as a_i, c_i, β_i involves in the process of optimizing the value of fit amid φ and data.

3.2. Artificial potential field

APF method provides better establishment and efficiency in the real time environment which is first introduced in the year 1985 [27]. Large scale data is not required for pre planning stage whereas utilizing objects to aware about environment more effort is required. Because of its simplicity APF is utilized more for home and real time planning [28]. Some loopholes are identified with classical APF method [29]. For overcoming such limitations traditional APF is enhanced by carrying various research works [30]. In addition, classical APF is collaborated with the algorithms used for optimization [31]. In some cases,complexity level of computation seems high. Increase in the time taken for computation decrease the performance of APF in real time environment. In this proposed framework APF is implemented in order to avoid obstacles by omitting the loopholes of traditional APF. It provides better result in the performance of obstacle avoidance. Basically, potential methods are implemented on the basis of potential function assignment. Potential function is defined as the mapping of relations amid obstacle allocated and no obstacle regions. Potential function frees the space and allows forcing because of potential field. Aim and repulsion of obstacle are computed parallel and cumulative force gradient is guided. Representation of potential field is as (4):

$$U_t(X) = U_a(X) + U_r(X) \quad (4)$$

where, in the above formulae, $U_t(X)$ represents total potential in the state X, $U_a(X)$ represents attractive potential in the X, and $U_r$represents repulsive potential at state X. Given $\nabla U_r(X) = -\sum_{all} f_{r,i}(X)$, which represents the virtual attractive force, further the force field at state can be denoted as (5).

$$f_t(X) = -\nabla U_t = f_a(X) + \sum_{i=1}^{all} f_{r,i}(X) \quad (5)$$

Similarly, Hamilton–Jacobi–Bellman (HJB) function is formulated as follows [32]:

$$minu(V(X), u) = -1 \quad (6)$$

where, represents the control and $V(X)$ represents potential factor. Unique global minimum value is computed from this function which implies the possibility of obtaining global feasible path even in exceeding status of local minima [33], [34].

3.3. Path planning

UAVs are controlled in some authenticated remote location which to utilize already planned air ways or dynamic paths. Collision avoidance and optimal path selection are mainly aimed while commencing the operation. In real time environment probability of static or fixed route is very low and dynamicity in path selection is preferred by considering low cost [35]. In real time dynamic environment, UAVs face various challenges to obtain optimal path. Path length, optimality, integrity, cost, time, energy, stability and collision avoidance are the most important challenges to be considered during path planning. Intelligent UAV path planning framework is implemented by utilizing the key features of both ANN and APF. Ultimate aim of this proposed framework is to attain optimal path by avoiding the hindrances. Figure 3 shows portraits the proposed framework for UAV path planning. By observing the salient feature, APF is utilized in this proposed framework because of its quickness, minimum computation cost and better performance in real time dynamic environment. Obstacle avoidance is mainly handled by APF to attain optimal path. After data is collected from various resources obstacle model is defined with the help of APF and then further outcome of the model is sent as the input as well as training parameters for the artificial neural network. Before the creation of model data is collected, processed and manipulated usually. Hardware components involve in the process of collecting data. Data collected from the real time adversarial environment is sent as input for the obstacle model which is built by the employment of APF.

Outcome of the obstacle model is provided as the input for ANN. The proposed ANN architecture is modified and subjected to have three-layer architecture. The first layer is the generic input layer, second layer is the hidden layer whereas the third layer is the output layer. The estimated cost function utilized in the ANN is mean square error and the optimizer function used is stochastic gradient descent. For the better performance the neural architecture is modeled to run feed forward and backward propagation (with kernel dimension of 3*3 and 5*5) to achieve better performance. The rule sets are defined in the back propagation in order to proceed the ANN. Input layer removes the unwanted data from the pooled data on the basis of filtering irrelevant data. Training parameters are defined in this stage which will be more useful for initializing path planning process and optimal path detection. Multiple operations are performed by hidden layers. In training part patterns are obtained from the data given. Outcome produced from the data is checked with the desired outcome while implementing supervised learning technique. Figure 4 shows the optimizer kernel loss. Form the Figure 4 it is clear that the loss function utilized for the proposed ANN specific to the path planning achieves a minimal loss which is negligible.

Based on the output parameters, the further process like new environment identification, path detection and constraints checking are performed in the same order. While analysing the constraints two different routes are defined. First one defines the optimal path where there is no collision and it is recommended for UAVs. On other hand if any adversarial conditions identified i.e. danger situations then those threats are again sent back to read once again with the help of APF for avoiding the obstacles. Optimal path is defined in terms of collision free path by evading obstacles and safe communication in the dynamic communication system with low cost of energy.

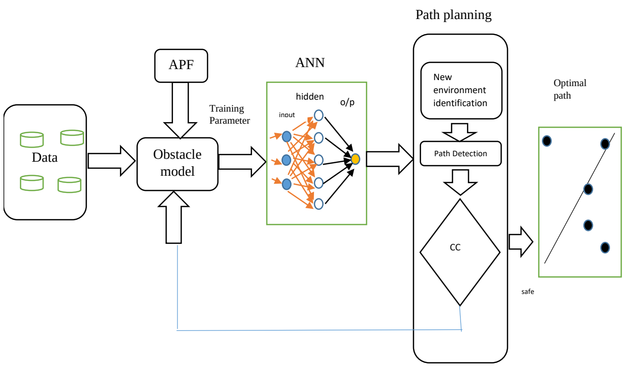

Figure 3. Intelligent UAV path planning framework

Figure 4. Optimizer kernel loss

3.4. Experimental setup

The proposed framework is successfully experimented in a self-developed simulated environment. The entire simulation tool is built using Python 3.7 with various libraries such as Gurobipy, Matplotlib, Scipy, and Numpy. The entire experimentation is carried with the single UAV. Further, the simulation scenario is carried out for two cases, i) with the stable network, and ii) with the instable network. In the second case, various validations such as node failure, jitter, and node reformation rate estimation, are carried and monitored. To prove the efficacy of the proposed framework, the resource monitoring is carried out for both the scenarios. The entire setup is utilized to execute all the state-of-the-art algorithms, analysing all the performance metrics and compared with the proposed framework.

4. RESULTS AND DISCUSSION

Figure 5 shows the simulation run of the proposed framework. The configuration of the UAV consists of the user level specification where the user can specify the drone configuration properties. The proposed framework takes care of algorithmic execution to be used for path planning. Further, the simulation run is clearly animated and the validation is performed with the static obstacle placement. Furthermore, it is proven that the proposed frameworks applied on the UAVs are capable in performing efficient path selection and obstacle avoidance. In addition to this validation, a dynamic obstacle placement is also carried out to test the efficacy of the algorithm. From the results it is shown that the proposed framework achieves with an accuracy of 93% in average for dynamic obstacle placement and 100% for static obstacle placement. The evaluation metrics analysed for best case, average case and worst case are listed in Tables 2-4. The evaluation metrics includes basic primitives of UAV (time, success of take-off, work, up start), altitude of the flying UAV (higher limit, Lower limit, euclidean distance and angular distance). Table 5 shows the performance analysis of the proposed method with the state of the art methods.

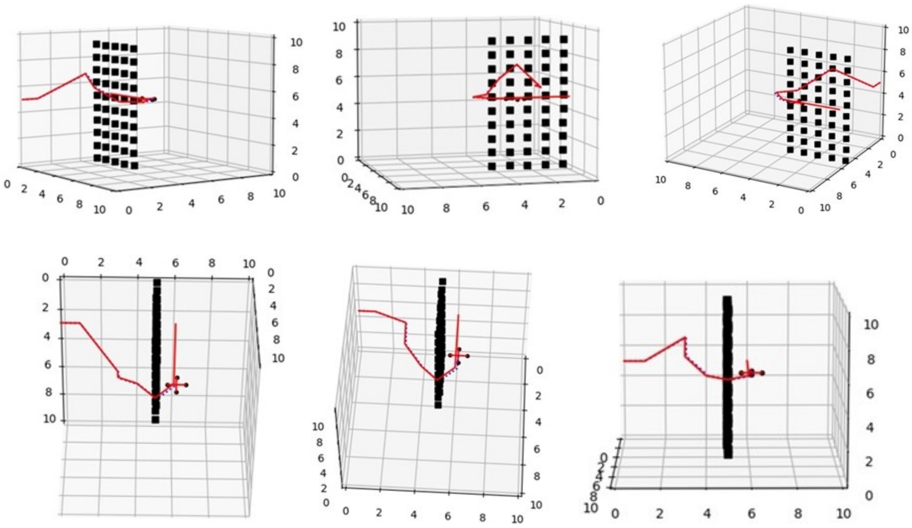

Figure 5. Simulation run of the proposed framework with static obstacle placement

Table 1. Symbols description

Symbol	Description
x_n	Input
w_n	Weight
$U_t(X)$	Total potential
$U_a(X)$	Attractive potential
$U_r(X)$	Repulsive potential
$\nabla U_r(X)$	Virtual attractive force
$f_t(X)$	Force field
$V(X)$	Potential factor
u	Control

Table 2. Evaluation metrics for best case

Evaluation metrics	Min	Mean	Max	Std
Average accuracy	0.98	0.98	0.98	0.98
Time	0.015	0.614	4219	0.997
Success	1	1	1	1
Work	0.606	0.863	1.151	0.089
Up start	1.228	5.412	20.391	4.815
Higher limit	15	146	573	143
Lower limit	17	162	593	149
Euclidean distance	1.007	1.45	3.248	0.557
Angular distance	5.084	8.72	16.53	2.655

Table 3. Evaluation metrics for average case

Evaluation metrics	Min	Mean	Max	Std
Estimated accuracy	0.64	0.64	0.64	0.64
Time	0.005	0.029	0.086	0.019
Success	1	1	1	1
Work	0.613	0.718	0.793	0.039
Up start	1.258	2.116	4.981	0.815
Higher limit	13	37	85	16
Lower limit	14	43	90	18
Euclidean distance	0.837	0.944	1.143	0.077
Angular distance	2.048	3.176	5.744	0.857

Table 4. Evaluation metrics for worst case

Evaluation metrics	Min	Mean	Max	Std
Estimated accuracy	0.19	0.19	0.19	0.19
Time	0.284	0.453	1.113	0.185
Success	TRUE	TRUE	TRUE	TRUE
Work	2.791	3.228	3.504	0.141
Up start	31.037	35.638	41.723	2.931
Higher limit	96	117	166	19
Lower limit	95	116	165	19
Euclidean distance	6.568	7.013	7.765	0.301
Angular distance	19.982	23.763	27.972	2.416

Table 5. Performance analysis of the state of the art methods vs proposed method

Approach	Min accuracy	Max accuracy	Mean accuracy	S.D accuracy
The proposed framework	0.947	0.930	0.935	0.943
Cruz-García *et al.* [7]	0.710	0.469	0.896	0.798
Liu *et al.* [16]	0.808	0.598	0.698	0.699
Yao *et al.* [17]	0.8913	0.809	0.78	0.72

5. CONCLUSION

In this paper Artificial Intelligence employed path planning framework is proposed with the goal of obtaining optimal path for UAVs without any collision. Obstacle avoidance is mainly concentrated in order to ensure the optimality of path. In this framework ANN and APF are playing vital roles. Obstacle avoidance is performed by APF and artificial neural network model is implemented for attaining optimal path for UAVs. Outcome of ANN is utilized for path planning and detection by considering the constraints. The final and ultimate outcome is optimal path for UAVs. Earlier existing methods implemented for UAV path planning are studied and the loopholes are focused. While comparing the implementation results of the proposed framework it provides better performance than existing schemes and also provides optimal and safe path as output at the end.

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