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Support Vector Machine Based Design and Simulation of Air Traffic Management for Prioritized Landing of Large Number of UAVs

Ahmed Abdulhameed and Qurban A. Memon

ABSTRACT

UAVs also known as drones are gaining more popularity day by day and its applications keep increasing. They are being used in several areas, such as transportation, surveillance, defense, etc. They open doors for new innovative applications due to their compact design, flexibility in landing and departing, the accurate possible control of their flying methodology. As a part of expected future of extensive use of this device, a landing control system for prioritizing the landing of large number of UAVs at a certain station using support vector machine learning is proposed. The proposed system shows promising results in terms of controlling landing sequences of a large number of UAVs. Based on results, the conclusions are presented.

Keywords: Drone, Landing Sequences, Machine learning, Support vector machine, UAV.

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I. INTRODUCTION

Unmanned aerial vehicles (UAVs) or the drones as commonly named, are part of the envisioned Urban Air Mobility (UAM) air transportation concept [1]. Currently, a large number of UAVs are being adopted for various applications that range from military (anti-terrorism operations, target localization) to civilian (transportation, surveillance), industrial monitoring, disaster relief (damage assessment) and agricultural services. Part of this futuristic concept that still requires intensive research is the landing of large number of UAVs. The autonomous UAV landing could be the most challenging part of controlling it because the controller has to generate trajectories that not only should reduce the power consumption, but also should withstand the difficult, unstable air dynamics, and least but not last the detection of the landing site [2]. A controller that can generate landing sequence for high traffic of UAVs to a certain landing zone is of a high demand and caused our interest to conduct research in this direction. Much work has been done [1], [2], but the current designs still face challenges, like flexibility and scalability. The flexible and scalable landing plan for a large number of UAVs is not addressed much in literature, though research reported briefly addressed it amongst other design challenges. The model proposed in [1] has a scalability issue due to the complex mathematical calculations that require long processing time, and thus carries limitation in real life applications that require near real time use. This part of the calculation can be taken to machine learning for training, simulated, tested in a working environment, and finally implemented in real life application. A lot of work involving UAVs for object tracking and other applications have been reported in literature. The reader is encouraged to refer to [2]-[4].

In this work, support vector machine concept was adopted to train the system using dataset generated based on the selected parameters. The objective here was to generate suitable landing sequences for large number of UAVs. For simulation purposes, we used 100 UAVs and considered the landing of the UAVs to be at each 10 seconds, so the system can prioritize up to 360 UAVs landing per hour unlike in [1], where the landing duration was around 1.5 hours for 80 UAVs.

The remainder of this paper is organized as follows. In section II, the literature review of landing of UAVs is discussed. The section III describes the proposed model and in section IV, the simulation of the proposed model along with selected design parameters is illustrated. The conclusions and future works are discussed in sections V.

II. LITERATURE REVIEW

The concept of controlling the landing of UAVs have been under study in the recent years. Some of the studies focused on the accuracy of positioning the UAVs at landing and withstanding the difficulties of the unstable, unpredicted air dynamics, and some other research works addressed topics related to UAVs landing control. In [5], a reinforcement machine learning (ML) model is proposed to partially enhance the issue of generating proper landing trajectories and was tested in both simulation and actual implementation using a real drone, and the results turned out to be a new contribution to this field. In [6], a k-nearest neighbor (KNN) based control model was implemented and tested to overcome the low accuracy of sensors against the changing wind speed on a VTOL UAV and using a real-life training data set. The implementation results on an actual drone showed robustness against the changes in wind speed. In [7], a new method for landing drones on an urban area with low GPS coverage using low-cost camera and deep learning techniques for mark detection were implemented, and its results surpassed the previous similar works despite using a lower cost camera. The authors in [8] used a convolutional neural network (CNN) to implement pose correction and autonomous landing using the inertial measurement unit (IMU) and visual sensors measurements. The work in [9] targeted autonomous driving of UAV using a low quality down locking camera based on reinforcement deep learning, and the results on implemented system outperformed the human pilots. In [10], a vision-based target detection and pose correction model implemented an autonomous landing. It used the inputs of the on-board sensors and IMU which was implemented on a Parrot AR drone 2. The authors in [11] attempted a successful landing with less than 37 cm on a moving platform of 12 m/second using model predictive control (MPC). The authors [12], [13] have proposed a safe landing mechanism in GPS denied environment using remote marker based tracking and visible light camera and empowered by convolutional neural networks. The results outperformed the object tracking methods both with and without neural networks in terms of accuracy and processing time. In [14], an Internet of Things (IoT) based command and control mechanism was implemented for round-the-clock surveillance system with automatic landing, and thus this prototype proved its feasibility. A similar work [1] targeted UAV landings by creating trajectories and a mathematical model for controlling the landing in urban area. The authors [1] stated that their proposed system can be further developed for better control of UAVs.

The work in this paper reports controlled landings for a large number of UAVs using a machine learning technique.

III. Proposed Model

The autonomous UAV landing control system proposed here is based on the idea that, for a certain application, and at rush hours, there will be so many autonomous UAVs coming back from duty to their station at the same time, and will be requesting for landing permit, so the control of their landing requires the controller's knowledge about the situation of each UAV to prioritize their landing sequence. In addition, it is also assumed that the landing UAVs can approach the landing pad from four different angles, where each landing point is located 90 degrees of angle from the nearer ones to reduce the chance of congestion and collisions. And that all these four points are considered at 500 m from the landing canter. The Fig. 1 below depicts the proposed specification of the landing area. In this system, it was also considered that the UAVs are landing on a moving belt conveyor with speed of one meter per second to give chance to the next UAV to land within a short time, typically set at 10 second. We also considered several other parameters to help the controller decide the sequence of landing. Below are the considered parameters.

a) Location (degrees) indicates the approaching angle from the landing station.

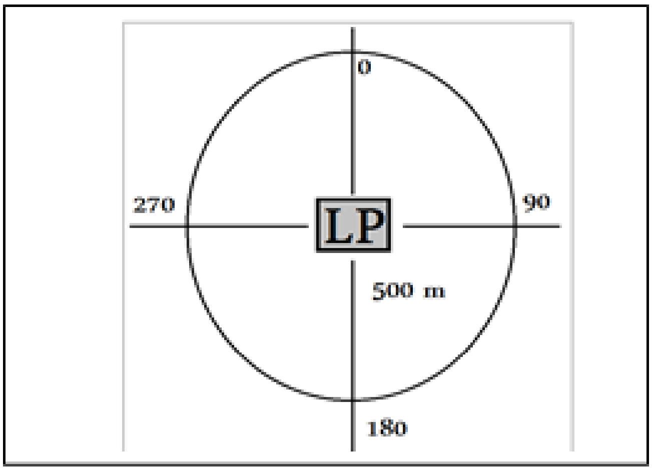

Fig. 1. The proposed landing area.

b) Battery charge: This parameter gives direct indication to the controller for how long this UAV will be able to wait before landing, so that the controller will have to select a higher priority if the battery charge is low. As a training parameter, battery life (seconds) indicates the expected remaining lifetime of the batteries.

c) Landing cost (seconds) indicates the cost for flying around the landing station to select the suitable angle for starting the landing process.

d) Mission criticality: Since the application considered in this research is general, so the system can assign higher priority to the UAV to land before others depending on the actual level of the mission. As a training parameter, criticality (1 critical, 2 not critical) indicates the criticality of the landing, other than the previous factors, which could be given for sensitive missions like (medical, military, etc.) missions.

e) Priority (Hi, Low) is calculated on the basis of criticality and battery lifetime, where all critical missions are Hi priority, and low battery drones (enough to land only) are Hi priority as well. All others are low priority.

f) Selected route (degrees) indicates the selected angle for landing, based on the cost of the route.

g) Approaching angle: Since four angles were considered: 0, 90, 180 and 270 degrees, thus the approaching UAV will have to report its angle position with respect to zero angle. This helps in selecting the nearest approaching point and estimate the cost to travel from the current position to the selected point. This will consume extra power and will require extra time. We considered the rotation in clockwise direction only, so that no two UAVs will be moving in opposite directions. The rotation speed considered here is one degree per second at the perimeter of the circle that has 500 m radius. Table I shows an example of the entered training dataset. These parameters became part of 100-sample training data set. In the next section, the details of implementation are explained.

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TABLE I: PART OF TRAINING DATASET FOR PRIORITY AND ROUTE

UAV No.	current loc. (deg)	battery life (s)	landing cost in route 0 (s)	landing cost in route 90 (s)	landing cost in route 180 (s)	landing cost in route 270 (s)	Criticality	Priority	Selected route
UAV-1	0	300	0	90	180	270	1	Hi	0
UAV-2	45	300	315	45	135	225	1	Hi	90
UAV-3	90	300	270	0	90	180	1	Hi	90
UAV-4	135	300	225	315	45	135	1	Hi	180
UAV-5	180	300	180	270	0	90	1	Hi	180
UAV-6	225	300	135	225	315	45	1	Hi	270
UAV-7	270	300	90	180	270	0	1	Hi	270

IV. IMPLEMENTATION

The process of controlling the landing and generating landing sequence is implemented based on an algorithm that has several steps, some of them were calculated using MATLAB, while others were decided using Multi-Support Vector Machine (M-SVM) algorithm. The algorithm used is one-vs.-one multiclass support vector machine (SVM) algorithm. It uses binary learner. Mathematically, it is defined as [16]:

$$Q = \frac{1}{2}\|w\|^2 - \sum_i \propto_i [y_i(\overline{w}.x_i + b) - 1] \qquad (1)$$

where $\propto_i$, x_i, y_i, b, w represent multiplier constant(s), input, output class (+1/-1), bias, and resulting weights once Q is minimized [16], and:

$$\sum_i \propto_i y_i = 0\,,\ where\ 0 \leq \propto_i \leq C\,; \qquad (2)$$

where C being a constant, is satisfied. The resulting weight vector and the decision is for "+" class calculated as [16]:

$$\overline{w} = \sum_i \propto_i [y_i(x_i)];\ (\sum_i \propto_i y_i \bar{x}_i.\bar{u} + b) \geq 0, \qquad (3)$$

The coding matrix is K×Q matrix, where K is the number of classes and Q is the number of binary learners. The algorithm works in a way such that all class data are compared two at a time until each class turns out to be unique. Its classification architecture is shown in Fig. 2. For illustration purposes, in Fig. 2, the SVM network is shown with a total of 2 layers, and the bias in set to zero by default.

Various equations were tried like linear SVM, quadratic SVM, cubic SVM, Fine Gaussian SVM, etc., but quadratic SVM and other higher order polynomials produced 100% accuracy during training. Two different training procedure were conducted: one for priority and another for landing route selection. Each implementation step uses specific inputs and decision process. The steps of the algorithm are as follows:

a) The approaching UAV will report its position, mission criticality and battery percentage.

b) Calculation of battery life will be made. It was assumed that the power consumption is 1%/60sec in steady state, rotation and soft landing (landing speed 5m/s), and it is 2%/60 s when hard landing (speed 10m/s) is being implemented.

c) Calculation of cost to reach each approaching point will be made.

d) The priority of landing will be evaluated based on the battery life and mission criticality. It was considered that there are two priorities. High, when the mission is critical, OR when the battery charge can stay for 250 seconds or less; Others with low priority. The idea here is to have a landing schedule for 25 UAVs in 250 seconds, during which time a new list of other 25 UAVs will be selected for next landing. Thus, scalability for the system is supported to continuously generate landing sequences for significantly large number of UAVs within a time frame.

e) The battery life and positions costs will be entered to another SVM to select the best landing zone from the available four points.

f) Once the top 25 are selected, and the landing zone for each one is selected, the corresponding battery life is entered into a sorting algorithm to select the sequence from 1 to 25, based on the lower battery charge.

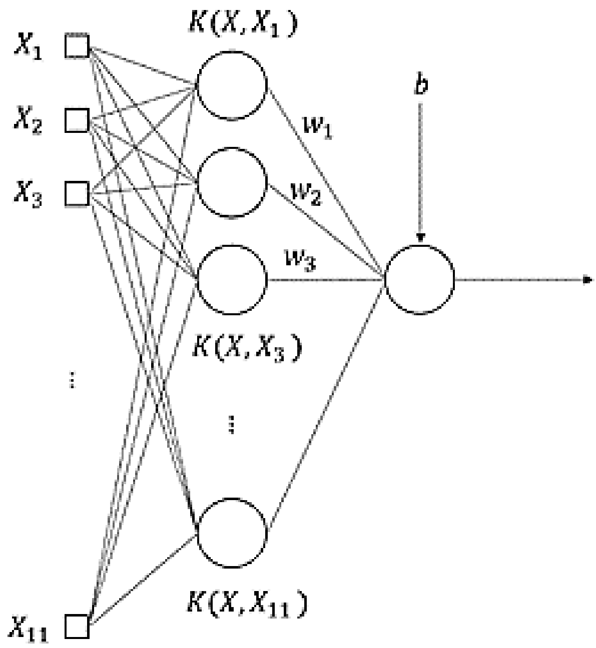

Fig. 2. The architecture of SVM used in this case.

TABLE II: ERROR LOSS VERSUS DIFFERENT KERNEL FUNCTIONS

Kernel	Error loss
Gaussian	1.5%
Linear	8%
Polynomial (order 2)	0%
Polynomial (order 3)	0%
Polynomial (order 4)	0%

In the above implementation, some actual life issue that can affect the landing of the UAVs were ignored, like air dynamics, traffic control, collision avoidance, position estimation and distance calculation, being out of the scope of our study. A number of studies [6], [8], [10], [17]-[19] have already discussed these issues in detail and proposed solutions accordingly. Likewise, details on landing on a moving belt conveyor was not discussed. The interested reader is referred to [11] for related study.

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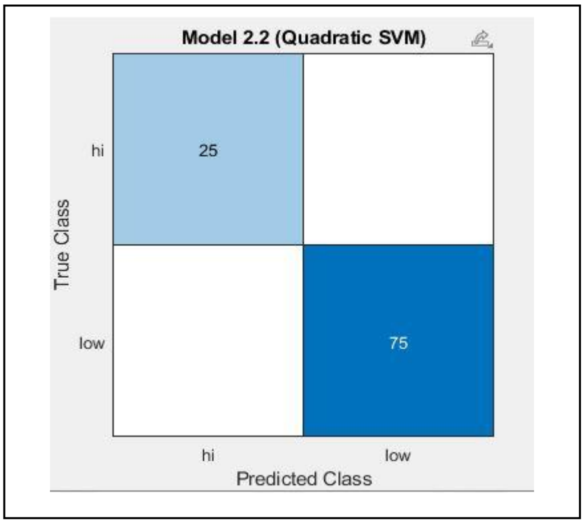

Fig. 3. Confusion matrix for resulting priority selection.

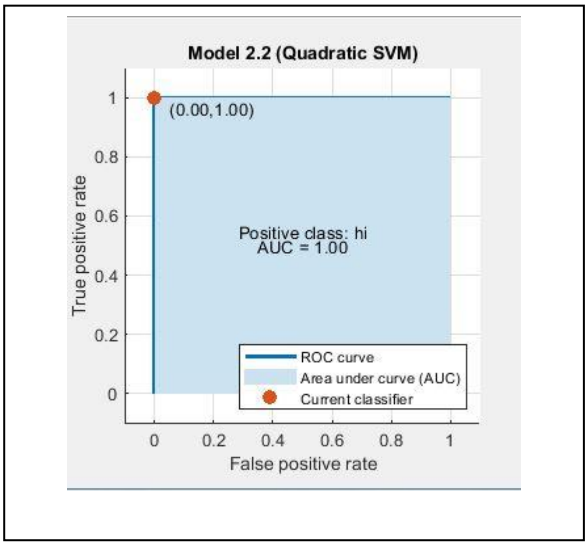

Fig. 4. Area under curve for percentage of correct results.

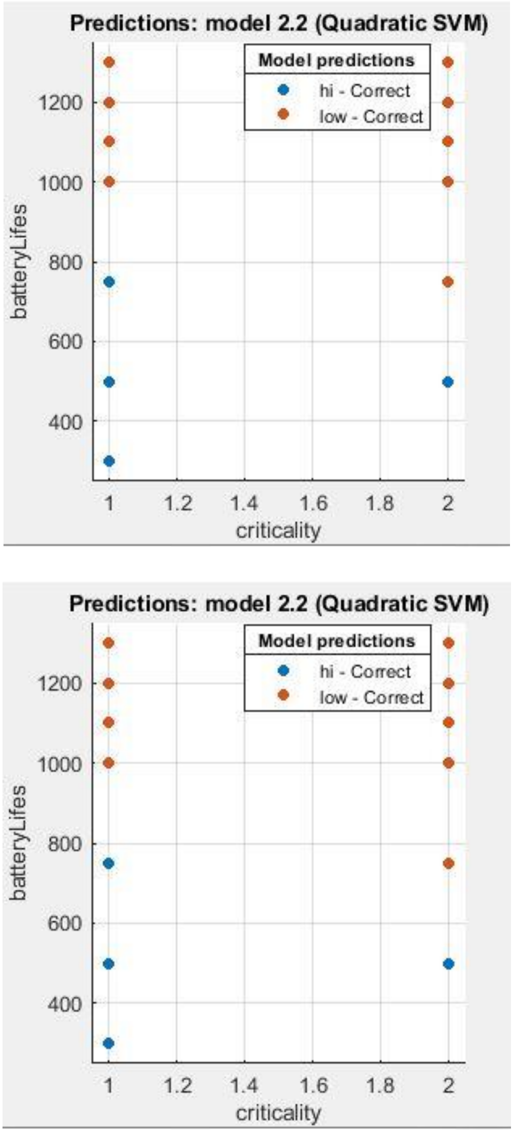

Fig. 5. Scatter Plot for classified (top) selected route (bottom) high/low priority.

The implementation has illustrated the focus on machine learning technique in solving such problems as it requires less online processing time and less modelling effort as compared to the system proposed in [1]. The results of our implementation are shown in Fig. 3, 4 and 5. The Fig. 3 shows the result of the priority classification of 25 number of UAVs that have been selected with high priority. The Fig. 4 depicts the area under curve for percentage of correct results. The ultimate result of SVM implementation to the input data was to select top 25 higher priority UAVs to initiate their landing sequence. This was correctly done via SVM algorithm. The area under the curve shows the percentage of the correctly classified UAVs as the 25 highest priority, which was “1”. The Fig. 5 shows a scatter plot for the classified high/low priority. In this scatter plot, it can be seen that the SVM classified both the critical and non-critical missions as high priority (blue color) when their battery life were low, but for the other battery life, it selected only the critical ones as high priority. Of course, not all critical are high priority, because we were limited to 25 UAVs only, as per the design of the system. All these figures show that SVM classifier has perfectly classified the data.

V. Conclusions

In conclusion, we proposed and simulated a UAV landing control system that uses machine learning techniques in acquiring information and generating landing sequence for landing a large number of UAVs on a moving belt conveyor. The proposed system can land up to 360 UAVs per hour on a single landing pad. This number can be increased by changing some of the considered parameters. This work proved that machine learning techniques can strongly impower the capability of the model to be fast, scalable, flexible, and easy to implement, as compared to the traditional mathematical models. The discussed parameters are easy to modify, and additional ones can also be added based on application requirement. This feature adds scalability and flexibility of the machine learning technique implemented in the study.

As a future work, more precise parameters and actual real-life training dataset can be used. Larger number of UAVs and landing pads can be studied for multiple and simultaneous landing control. Other types of machine learning techniques and deep learning techniques can be studies. Also, a specific application with real data can be addressed in a future work

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to have better understanding on the capability of the proposed system.

CONFLICT OF INTEREST

Authors declare that they do not have any conflict of interest.

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