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NEURAL NETWORK FOR AUAV LANDING USING STOCHASTIC GRADIENT DESCENT ALGORITHM

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Abstract

Landing an AUAV on a ship deck platform is one of the most researched topics in the field of unmanned vehicles. Small fixed-wing AUAV with 250 landing passes are considered with no cross-wind disturbances. Mean Time for landing and taxing of AUAV on ship deck platform (though highly dependent on dimensions of Carrier Vehicles) is assumed to be of 45 seconds duration. AUAV response time is 16 seconds whilst carrier vehicles have only 21 seconds for both sea wave dynamics and AUAV movements. Deep Stall landing procedure is incorporated into the control algorithm owing to its high risk and high performance in a time-constrained environment. Six data points are considered while implementing the SGD Algorithm during Glide Phase. Γ is assumed to be 0.3 for optimal result. Carrier and AUAV State estimation is derived by sensor data using GPS, Optical Electric Color sensors (onboard AUAV) for Fresnel lens (Carrier), IMU etc. The Control Algorithm used Feed Forward Propagation with the landing prediction GO in 74.4% and NO GO (Turn Around) in 11.6% and failures in 14% cases.

***Keywords*:** Stochastic Gradient Descent Algorithm; Autonomous Unmanned Aerial Vehicle; Ship Deck Platform.

抽象的

将 AUAV 降落在舰船甲板平台上是无人机领域研究最多的课题之一。具有 250 次着陆通道的小型固定翼 AUAV 被认为没有侧风干扰。 AUAV 在舰船甲板平台上着陆和征税的平均时间（尽管高度依赖于运载工具的尺寸）被假定为 45 秒持续时间。 AUAV 响应时间为 16 秒，而运载工具对于海浪动力学和 AUAV 运动的响应时间仅为 21 秒。深度失速着陆程序因其在时间受限环境中的高风险和高性能而被纳入控制算法。在 Glide 阶段实施 SGD 算法时考虑了六个数据点。 Γ 假定为 0.3 以获得最佳结果。载波和 AUAV 状态估计是通过使用 GPS、光电颜色传感器（机载 AUAV）用于菲涅耳透镜（载波）、IMU 等的传感器数据得出的。控制算法使

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用前馈传播，着陆预测为 74.4% 和 NO GO（转身）在 11.6% 的情况下，在 14% 的情况下失败。

关键词：随机梯度下降算法；自主无人机；船舶甲板平台。

1. Introduction

This paper discusses implementing, Neural Network predictor for Landing Assisted Control algorithms for Autonomous UAVs (AUAV). The sensors data on the AUAV's rely on the Inertial Navigation System, LiDAR data for landing, Cameras relayed to Ground/ Aerial Tracking Systems. Takeoff and Landing are the most difficult and error-prone stages. 54% of aircraft (manned or unmanned) accidents [1] are attributed to landing & its associated problems.

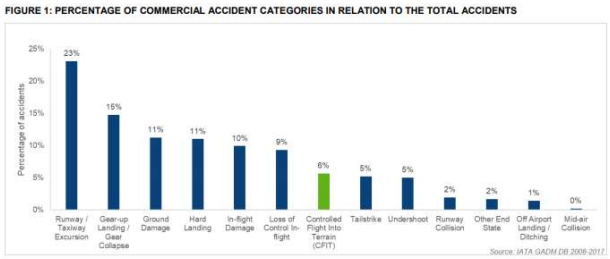


Figure 1(a) – ICAO Safety – Commercial Airline Accidents Reasons

The risk factor exponentially increases with Short Takeoff and Landing (STOL) and especially on Carrier platforms. The Oscillating motion produced due to sea waves and oceanic currents of the carrier vessel result in asymmetric heave (pitch), roll, and yaw (sway). Carrier vessels having one or many runways are compensated in heave and roll for AUAV deck operations. The Carrier deck has a catapult launch system along with a landing cable arrestor system to accomplish various Short Takeoff and Landing (STOL) operations. The carrier deck on its Port Side is fitted with Fresnel Lens to indicate the State estimation of the incoming flights. In conventional carrier systems, the Landing Signal Officer (LSO) indicates whether to proceed with Landing (GO) or abort landing (GO AROUND) to the incoming flights. In the case of AUAV, the Color Sensor fitted on the AUAV identifies whether the bearing is in line with the Carrier deck for landing or high. Necessary Correlative Measures with pitch, roll and yaw are performed to align with carrier deck for landing.

2. Problem Definition

Landing is the one of the most dangerous and critical phase during AUAV navigation; which needs efficient planning and control for smooth and safe landing. Landing (STOL) depends on the neural network prediction either to land/ abort landing thereby giving necessary [pitch, roll, yaw] commands to the Autopilot to accomplish the task using SDG Algorithm.. Deep Stall Landing [2] methodology is exercised during Glide Stage wherein $Angle_{Attack} > Angle_{Glide}$ thereby the Vehicle loses its altitude/ height drastically; incorporating pitch corrections in order to sustain flying. An accurate control algorithm is a prime requisite in such situations. A Delta wing structure is selected for its agility and maneuverability.

Conventional Wisdom suggests a 28 seconds window period prior to any control failure happening. The functioning and working of autonomous flight controller depends on the specific actions to be taken while attempting dynamic conditions which are onset during AUAV navigation; erstwhile which are non – programmed in fault-tolerant system, owing to their dynamic nature. A Neural network

predictor with resultant [pitch, roll, yaw] suggestions is considered in this paper; which serves as a main command source and initiation. The outcome is fed into the Autopilots control programs and feedback controls for bounded error compensation. It could be emphasized that the resultant control system would be capable enough for self-logical analysis & its own decision making basing on domain knowledge that mimic human behavior and correlative actions in securing higher performance.

The Neural network is designed using a single hidden layer feedforward function. The simulation results predict/ demonstrate that the proposed neural fault-tolerant system is capable enough to achieve safe landing.

Mathematical Modelling [3]

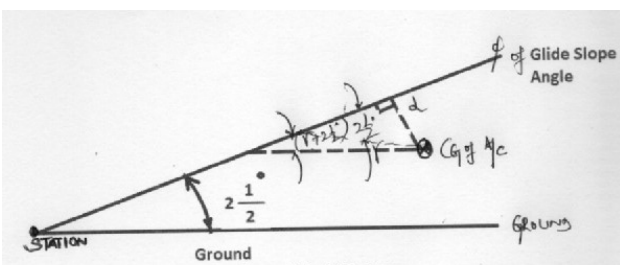


Figure – 1(b) : Glide Phase

$\hat{U} = U\sin(\Gamma + 2.5) = U(\Gamma + 2.5)/53.7$

$\Gamma = 57.3d/ R$ deg.

d -> glide slope angle. It could be either +ve or -ve wrt VOR transmitted beam angle
E -> deviation from slant distance

The final phase of AUAV Landing requires the transition from approach at glide start point to touchdown point during Flare stage. From Glide phase to Flare phase, the descent rate is increased exponentially.

The flare control system controls the flare altitude/ height rate h_r by fine adjusting pitch angle.

Figure 2 - Block Diagram of Glide Path

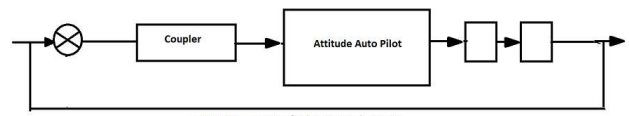


Figure 3 - Automatic Flare Control System

1. Small Size Drone[5]/ AUAV Landing,

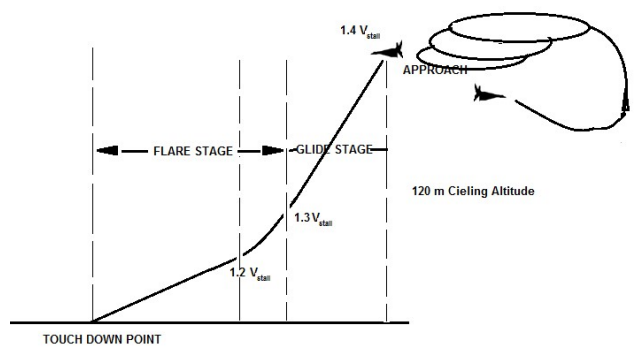


Figure 4 – Various Stages of Landing Phase

Landing is divided into three phases viz.

a. Approach Phase – AUAV is vectored to descend from cruising altitude (Top Descent Point (TDP)) i.e. 350 feet to 250 feet referred to as STA (above ground level) at algorithmically computed descent rate in feet under influence of wind factor, temperature this is done prior to reporting to Autonomous Air Traffic Controller (ATC-A).

b. Glide Phase – At 250 feet altitude AGL; the guidance system vectors the AUAV to interpret the Fresnel Lens Height Adjustment at a distance of 1.8 km from the runway. The autopilot positions the

aircraft so that it is on heading towards the runway centerline (lateral guidance).

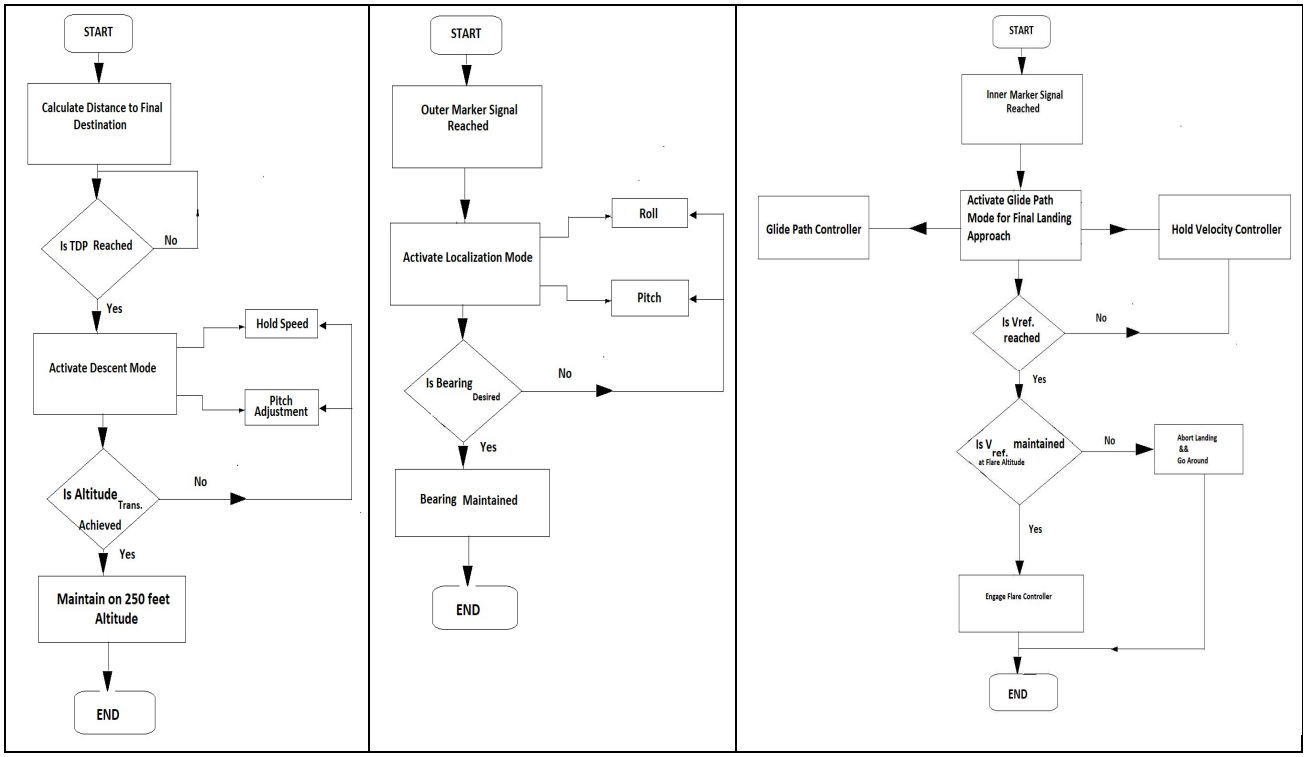


Figure 5 – Flow charts for Control Algorithm

During Landing in RPVs, autopilot is switched off whilst in our case; the automatically is engaged when the AUAV approaches Inner Marker. A Glide Scope path is generated which the AUAV at an angle of 2.5^0 to the landing platform. In this stage, the approach velocity varies from 1.4 x V_{Stall} @ Outer Marker to 1.2 x V_{Stall} at flare initiating point. At50' above runway Flare Mode is initiated and continues till touch-down point.

2. *Stochastic Gradient Descent Algorithm (SDG)* [4]

It is one of the most commonly used optimization algorithms in Machine Learning. The trace shows that, at each iteration, the parameters are updated in the reverse direction of the objective function *J(w)* in lieu of the input parameters Learning rate (α) is determined by the size of the step taken on each iteration to reach the local minima. The procedure is followed along the downward direction of the slope until the local minima is reached. The following is the procedure used;

a. Give any number (randomly) to weight *w* and bias *b*.
b. Assume learning rate α to be 0.01.
c. Let μ = 0 and σ = 1 and scale dataset accordingly
d. On each iteration, *∂(J(w))* for each gradient value.
e. For the slope, if *w > 0*, indicating the righteous direction for obtaining the optimum *w**. If f(update)< 0 then, we

are closing onto the optimum values of w^*. Similarly, if the value is negative, then an update is positive and results in w convergence to optimum value of w^*

Pseudocode for SGD in Python:

```
def SGD(f, thetainitial, alpha01, no_iteration):
#       Arguments:
#       f                -- optimization function, single argument -> two outputs viz. a cost and arguments
#       thetainitial     -- initial point of SGD from no_iteration – no. of iterations to SGD to run
#       theta            -- the final parameter value of SGD algorithm
    start_iteration = 0
    theta = thetainitial
    for iteration in xrange(start_iteration + 1, no_iteration + 1):
        _, grad = f(theta)

        theta = theta - (alpha01 * grad)
```

$$\frac{x_i - \mu}{\sigma}$$

$$\frac{\partial}{\partial w} J(w) = \nabla_w J$$

$$\frac{\partial}{\partial b} J(w) = \nabla_b J$$

$$w = w - \alpha \nabla_w J$$

$$b = b - \alpha \nabla_b J$$

$$w = w - \alpha \nabla_w J(x^i, y^i; w)$$

3. Neural Network

A Neural Network is having two layers with eight neurons viz. Velocity, Pitch. roll, yaw, latitude, longitude etc.; the inputs to the network is a matrix [different ground speed, glide slope angle] and ascertained output is the prediction of GO/ NO GO i.e. GO is for landing while NO GO is for turn-around in either case the output gives the much needed descent rate to be maintained by the autopilot. The network is a simple feed-forward having hidden neurons (sigmoid). This algorithm typically requires more time during learning stage, but a generalized result is obtained for noisy and noiseless datasets. Training stops according to adaptive weight minimization (regularization). Here, for training 60% data is used while 25% for validation and the rest 15% for testing. The Mean Square Error (MSE) of the network is approximately 0.807, R-Value > 0.99 for total responses.

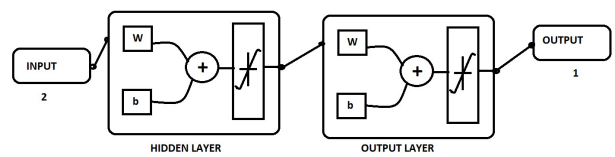


Figure 6 Hidden Layer

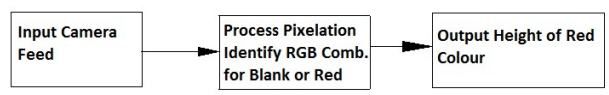
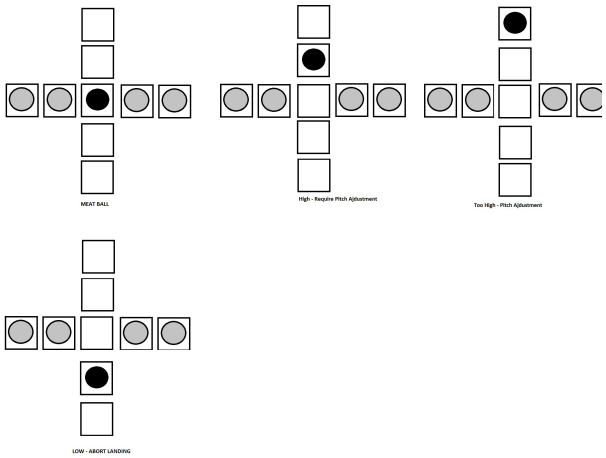


Figure 7 Fresnel Lens Height Decision

$$\begin{pmatrix} 0 & 0 & 0\,0 & 0 \\ 1 & 1 & 1\,1 & 1 \\ 0 & 0 & 0\,0 & 0 \end{pmatrix}$$

In Row(r) x Column (c) = 2 x 3 Meat Ball and Ready to Land identify each column value equal to all other i.e. All Lights Glow

3 x 5



4. Experimental Setup

AUAV has a ceiling altitude of 120 m for Small Drones under 2 kg total payload according to Director General Civil Aviation (DGCA), Govt. of INDIA [5] with a full thrust velocity of not more than 25 m/s. In this paper, we are using a single Heavy-duty Brushless DC (BLDC) motor with10 kg maximum thrust and a total payload of 1.875 kg. The wingspan of the Single Engine Fixed Delta Wing is 30.54 cm (1'), total length is 25 cm.

The Electronic payload includes Arduino Mega, GPS Module, IMU Sensor Module, Zigbee 2.5 GHz RF Transceiver, Color Sensor, Stereo Vision Camera (maximum Linear LOS 2 Km) with 210^0 FOV, Stepper Motors for Ailerons, Rudders, Elevators, Landing Gear, Altimeter etc., LiPo Battery Twin Pack.

Landing Platform:

The AUAV is programmed to land on a floating pontoon in Cavitation Tank. During the course of experiment, the wave height is gradually raised from 1.0 cm to 30.0 cm. The pontoon buoyancy reflects the same of an Aircraft Carrier at full course speed. Each 1.8 cm raise in wave height is approximately equivalent to 1.0 m of sea wave assuming wind speed to be 6 kmph. Deck Stabilization Algorithms are used employing Stewart Platform actuators. Sine Summation Sequencing Algorithm is implemented to predict the incoming wave and suggest necessary actuator logic to stabilize the deck platform. The Deck stabilization algorithms are extensive and out of scope of this paper and not discussed. Hence, it could be assumed that what ever the wave conditions; the deck remains fairly stable at all times easing the AUAV movements.

The Pontoon on the other hand, has Fresnel Lens fitted on the Port Side and tightly fixed to the bouys on either sides for stability during Cavitation Experiments. The Fresnel Lens tilt is $\pm$ 30^0 while back and forth movement is restricted only upto 30.54 cm.

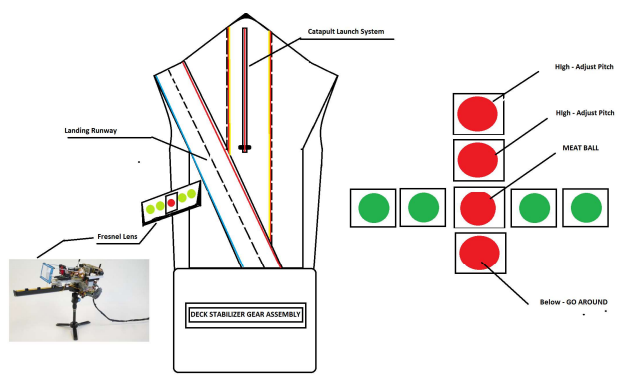


Figure 7 – Pontoon with Landing & Launch Pad

AUAV:

25 cm long Small Fixed Wing (Delta) Autonomous Aerial Vehicle having a wingspan of 30.54 Cm. The AUAV is single motor driven. Battery endurance at full thrust is 36 minutes and optimal results are achieved at 65% thrust for 45 min. A temperature difference from motor starting at launch till motor Off after landing for a single pass is ΔTemp. = 8^0 C. The temperature

difference dictates the battery consumption or draining capability.

The experiment emphasizes on the following,

a. take - off till landing is known as pass
b. common procedure is employed from take-off till approach stage
c. during approach, depending on the AUAV state estimation; the Final Approach and landing route plan is fixed.
d. Usual glide approach angle is 2.5^0, five different variants of glide are adopted viz. normal approach, Deep stall approach, Vertical drop down approach etc.
e. At outer marker i.e. 1.8 km from landing platform. The FAF is fixed.
f. The glide stage is initiated at this point.
g. The landing trajectory or path is ratified with the carrier vessel.
h. The Neural Network is triggered and which dictates the pitch, roll adjustment for landing. It is assumed that, there is no cross wind.
i. The Neural network must predict either GO i.e. to land or NO GO i.e. to abort landing and in either case project necessary pitch and roll adjustment for the Autopilot.
j. The weight of neural network prediction is heavily dependent on the following stages;
    a. Incoming Color Sensor data from the Fresnel Lens (Carrier) on board the AUAV
    b. deducing the inline alignment of the "Red" light in comparison with the green lights using stereo vision camera.
k. The landing pattern can be changed at any time from Outer marker till Inner Marker.
l. During Flare stage, if the landing is aborted then Left/ Right Thrombone Pattern is used to deflect the Inbound AUAV from the Carrier.

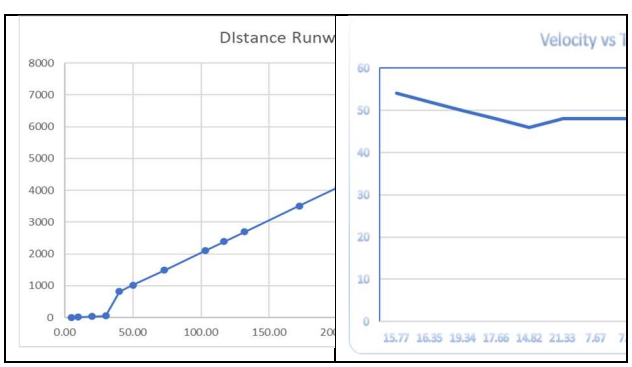


Figure – 8(a) – Runway Distance V/s Altitude Graph Figure 8(b) Velocity V/s Time Taken Graph

5. Conclusion

A Single Engine battery operated delta wing autonomous UAV is made to land on floating pontoon tugged in a cavitation tunnel. During course of experimentation, deep stall landing methodology is used to test the efficacy of the Neural network predictor. In total 250 passes are conducted over a period of 60 days under similar ideal conditions having nearly zero cross wind disturbance. Ceiling height of 350 feet is considered[5], Glide

stage commences at 250 feet altitude and flare at 50 feet AGL. The full thrust velocity of AUAV 60 kmph and operated at 65% and giving 40 kmph RMS Velocity. The stall speed is 25 kmph. Stochastic Gradient Descent Algorithm is backbone for Feed Forward Neural Network. The final results for neural prediction can be summarized as total no. of affirmative landing is 186, abort landing is 29, crash landing is 35. Thus, efficiency is 86%. Out of the Crash Landings, it had been observed that data starving (between Carrier and AUAV and vice - versa) is one of the reasons for control failure leading to Crashes. Further research is required in reducing the Crash Landing and work out on the optimizing the algorithm in reducing the complexity and thereby improving efficiency.

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