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SIMULATING AN ARTIFICIAL INTELLIGENCE FOR HELICOPTER FLIGHT MANOEUVRE

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ABSTRACT

The paper aims to simulate an artificial intelligence for helicopter flight manoeuvre. The methodology makes use of inverse simulation and genetic algorithms to develop a high level helicopter pilot model to fly a prescribed manoeuvre, and realisation of a multi-objective optimisation/search algorithm to converge to a human-like solution. The inverse simulation generates the controls required to fly the helicopter, while the genetic algorithms generate feasible solutions to the inverse simulation problem. The overall goal is to prescribe a manoeuvre for the helicopter and have the developed pilot find control settings that carry out the given manoeuvre. Continuous controls encoding method was implemented in flying an acceleration/deceleration manoeuvre form. The helicopter pilot was formulated as a multi-objective optimization problem with four objectives imposed as penalties. A novel approach, termed maxPenalty, compared and returned the biggest of the four penalties. The genetic algorithm attempts to maximise the fitness function, while minimising the pilot's total workload. The work evaluates the developed model pilot in terms of performance and functional efficiency.

Keywords*:* Genetic algorithms, Helicopter pilot, Inverse Simulation

INTRODUCTION

The focus of the work is to develop and simulate an artificial intelligence for a model helicopter pilot. Artificial intelligence is concerned with developing computational models for carrying out human-like tasks. The increasing complexity of helicopter's capabilities and information has also increased the demands and stress on the pilot flying it. This makes pilots encounter problems of information overload, and may be prone to mistakes. Issues that need consideration when flying a helicopter are situation awareness, cost and safety on the part of the pilot especially in dangerous missions, for example, testing of dangerous weapons [1] [2]. Realisation of this and the need to inculcate accuracy and stability in a given task form the main motivation for this work. The aim is to define tasks for the helicopter and have the pilot find control settings that carry out those tasks. The safety issue identifies the aerodynamic disturbances that affect the helicopter while approaching its target, and ensuring that both the risk and consequences of such disturbance are reduced to a minimum. This is especially true in the case of landing a helicopter in highly constrained locations like an offshore helidecks.

In changing from a given steady state to another, the helicopter should be able to maintain its stability through the coupling effects of the control inputs. The following makes helicopter model an interesting researchable problem [2] [3]:

- ⇒ It has multiple inputs and multiple controls;

⇒ The controls are cross-couples (application of one control has multiple effects on others, and produces motion in various directions);
⇒ It has six-degrees of freedom (rotates and moves in all the three directional axes);
⇒ Ability to impose constraints in velocity and acceleration.

The benefits of developing systems that will carry out inverse simulation such as this, is to simulate the real manoeuvre, and evaluate the resulting controls in terms of deviation from the reference trajectory, proximity to the target, and effects on pilot workload. The reason is in terms of cost and safety of the helicopter and pilot [2]. Genetic Algorithms (GAs) are special classes of artificial (computational) intelligence model systems that are similar to human process. In the present work, the inverse simulation generates the controls required to fly the helicopter, while the genetic algorithms generate feasible solutions to the inverse simulation problem using a search algorithm. The ability of GA in dealing with huge number of variables, simultaneously searching the entire parameter space in terms of the fitness of the individuals, providing a list of optimal solutions makes it a preferred choice of tool in realising the model pilot [4]. The fundamental goal of this research work is to evolve a human-like behaviour for helicopter pilot. That is, a system that should be capable of simulating the way a human pilot will fly a helicopter.

The general approach to helicopters and aircrafts flight simulation involves developing a computational model of the aircraft and calculating its response to a set of pilot inputs. But the inverse simulation, a technique for calculating the pilot's control inputs generates the control actions required to specify a particular trajectory the helicopter will fly. Unlike commercial flight simulators which are human controlled, problem specific, hence cannot be extended, there is the need to manipulate input data based on the observed response, and adapt the flight environment. Besides, the flight simulators generally are training software packages for pilots.

The overall question this work tries to answer is the possibility of a model pilot to fly a helicopter in a way resembling human pilot behaviour. There are many automatic pilots that can fly an aircraft, but most of them do not mimic human behaviour [5]. Simple designs of the pilot only apply to a predefined altitude and heading. Other more advanced designs will fly a path specified by the supervisor, a person that initiates the helicopter flight. The main requirement therefore, of this work, is to incorporate human-like behaviour in the development of a simulated non-human piloted helicopter flight. Algorithms that could be used to generate feasible solutions to the inverse simulation problem, in this case the helicopter's trajectory, will help in calculating the pilot's control settings.

The helicopter pilot simulation is a form of optimisation problem. Optimisation refers to the process of making something better. Its concern is in trying a lot of variations on an initial concept and using the information gained to improve on the idea [4]. An optimisation problem is a problem aimed at finding the optimal or near optimal solution from a specified set of feasible solutions using some measure for evaluating each individual solution. An algorithm to solve such problem is called an optimisation algorithm. In this present work, GA is the optimisation algorithm used to achieve human-like helicopter models. They are inspired by Charles Darwin's theory of natural evolution [6].

By natural process, species are evolved through selection and random mutation. They simulate the natural selection and variation approach, using it to evolve a better solution to a problem. GAs are popular techniques for multi-objective optimisation, in which the helicopter problem is formulated, having proved successful in a range of learning and optimization problems like travelling Salesman Problem, etc [7].

The helicopter model is represented by the state space equations which are in their original form. The general mathematical model of the motion is given by [3] as:

$$\dot{\underline{x}} = A\underline{x} + B\underline{u} \qquad (1)$$

Where $\underline{x}$, $\underline{u}$ and $\dot{\underline{x}}$ are the state vector, control vector and output vector respectively, and $\dot{\underline{x}}$ is the time derivative of $\underline{x}$, A is 9x9 linear coefficients of system matrix and B is 9x4 linear coefficients of controls matrix of the helicopter. The elements of the state and control vectors are:

$$\underline{x} = [\ u, v, w, p, q, r, \phi, \theta, \varphi, u_e, v_e, w_e, x, y, z\ ] \qquad (2)$$

$$\underline{u} = [u_1, u_2, u_3, u_4\ ] \qquad (3)$$

Where u, v and w are the linear velocities, relative to the body axes; p, q, r, the angular velocities; ϕ, θ, φ, the Euler angles for roll, pitch, yaw, respectively; u_e, v_e, w_e, the velocity components in the earth axes; x, y, z the linear distances over the ground all in the x, y, z directions; u_1 is the collective control; u_2 and u_3 are the lateral and longitudinal controls respectively; u_4 is the pedal control [2].

MATERIALS AND METHODOLOGY

The approach in this work makes use of inverse simulation and genetic algorithms to develop a high level helicopter pilot model to fly a prescribed manoeuvre, and realise a multi-objective optimisation/search algorithm to converge to a human-like solution. The inverse simulation technique is used to generate controls in an experimental situation, in this case where the helicopter does not exist. The controls can then be analysed to see if they work well in simulation. Different approaches have been utilised in the past to develop devices and systems for helicopter flights control. Examples include but not limited to: fuzzy logic control, genetic algorithms, neural networks, individual channel design, multivariable methods [2] [3] [8]. It is very necessary to establish the suitability of a particular approach for application to the helicopter pilot modelling.

Inverse Simulation for Helicopter Flights

Several approaches to the solutions of inverse simulation problems exist in literature. One approach models the helicopter flight as an optimal control problem, achieved through minimizing the difference between the desired and the achieved flight trajectories using a gradient method [9] [10]. This is achieved through two categories of algorithms: Differentiation and integration inverse methods. Differentiation inverse method uses numerical differentiation to evaluate the time derivations of the states, and computes controls directly from the differential equations; while the integration inverse method uses integration and Newton's iteration method to calculate the controls step by step. The helicopter's trajectory is discretised, and for a given step with known initial controls, the equations of motion are integrated with estimated controls at the end of the step. The errors, which are the difference between the actual and desired trajectories, are calculated, and the controls at the end of the step are adjusted using Newton-Raphson technique to reduce the errors to zero [9].

The Theory of Genetic Algorithms

In arriving at solutions to problems, GA combines two areas of research: Application of *selective pressure* to a *diversified population*. This principle results in the strongest among the members of the population dominating, a phenomenon called *survival of the fittest* [11]. A general workflow of a simple GA is given below:

1. Generate an initial population of chromosomes randomly;
2. Evaluate the fitness of each of the chromosomes in the population;
3. Based on the fitness, form a breeding pool by selecting the breeding chromosomes (parent chromosomes) from the population;
4. Crossover the parent chromosomes to produce offspring;
5. Mutate some genes in the offspring chromosome and place the resulting children in a new population;
6. Replace the parent population by the successor population and go back to step 2 above until a termination criterion, which is either a best chromosome is found or maximum number of generations is reached.

The flow chart shown in Figure 1 depicts a typical GA.

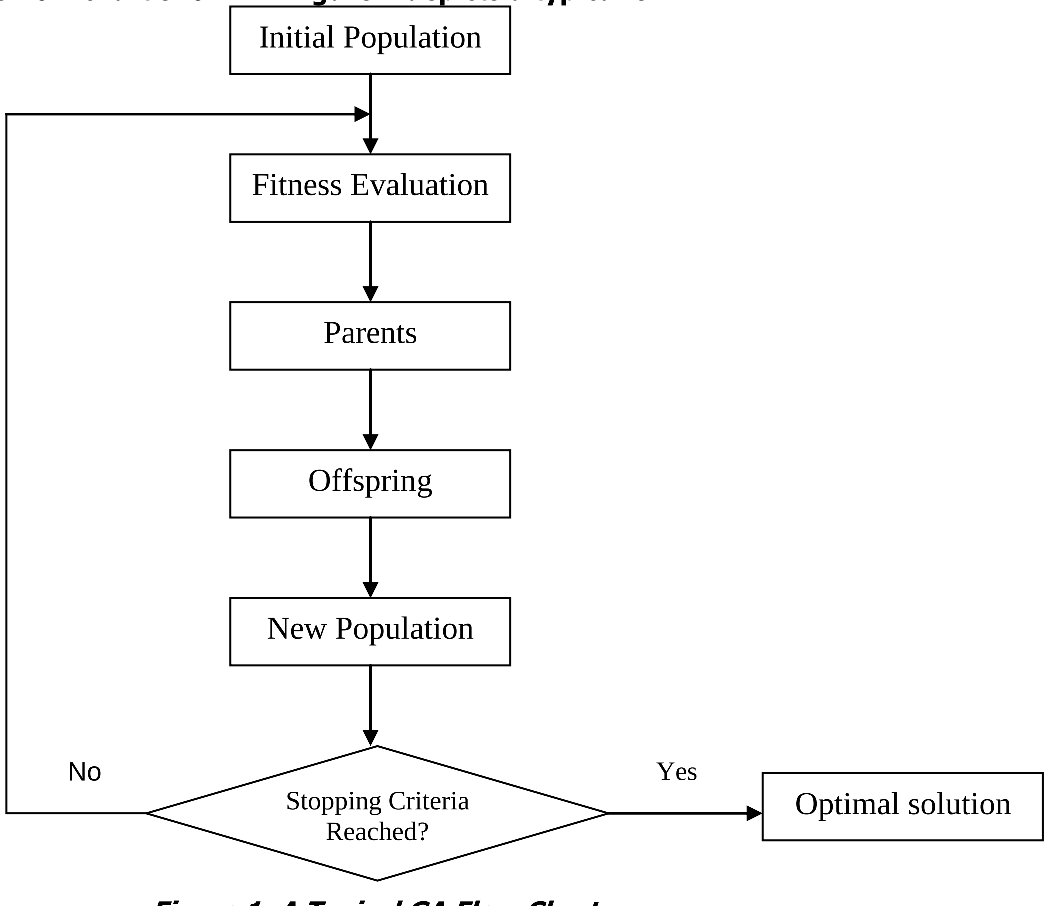


Figure 1: A Typical GA Flow Chart

Genetic Algorithms for the Pilot Simulation Problem

The prescribed manoeuvre in this work is acceleration/deceleration manoeuvre. It consists of the following tasks: Starts from hover, at a point; accelerates in a forward flight to the target distance along the $x-$directional axis; positioned at trim/hover, after a fixed flight time. In flying this manoeuvre, a pilot starts by displacing the cyclic stick forward, causing the nose to pitch down. This results in the increase in airspeed, increased power, and loss of altitude, with the collective control being held constant up till the maximum airspeed [12]. Once the target airspeed is reached, the pilot initiates a deceleration by pulling the cyclic stick backward, reducing the power, while maintaining a constant holding altitude. This causes the nose to pitch up, just before reaching the final stabilized hover [12]. Increasing the collective during this process of maintaining a constant airspeed will make the helicopter to initiate a climb, while decreasing the collective will cause a descent. A good coordination between the collective and cyclic control inputs (up/forward or down/backward respectively), will result in airspeed changing while maintaining a constant altitude.

A pilot will generally take the shortest path to the target. A penalty is designed to enforce this. The penalty, p_1 measures the trajectory's deviation from the x-directional axis, given by:

$$p_1 = \sum_{i=0}^{N} \sqrt{y_i^2 + z_i^2} \tag{4}$$

Where: y_i = distance along y-axis; z_i = distance along y-axis; i = time step, and N is equal to the maximum number of time steps. A second penalty, p_2 measures how close the pilot is away from the target. It is the deviation of the final horizontal distance from the target, and given by:

$$p_2 = \sqrt{(x_{target} - x_{final})^2} \tag{5}$$

A third penalty, the controls penalty ($p_{controls}$), aims at minimizing the total control movements, and hence the pilot's workload. This is because naturally, a pilot would act to minimize effort, and so this would give rise to human-like behaviour of the model pilot. The approach is achieved by summing the absolute values of changes in controls in each time. Mathematically, it is defined as:

$$p_{controls} = \sum_{c=1}^{4} \sum_{i=1}^{10} \left| \Delta u_i^c \right| \tag{6}$$

Where: $\Delta_i^c = u_{i+1}^c - u_i^c$ = change in value of control c at time-step i.

From the description, the manoeuvre started and stopped in hover. This means that the helicopter is at rest with zero velocity and acceleration at the end of the manoeuvre. For this reason, a fourth penalty was imposed on the velocity and acceleration, achieved by summing the squares of velocity and acceleration, given by:

$$p_3 = u_{final}^2 + \dot{u}_{final}^2 \qquad (7)$$

These give rise to the following *FourPenaltiesGA* in the calculation of the fitness:

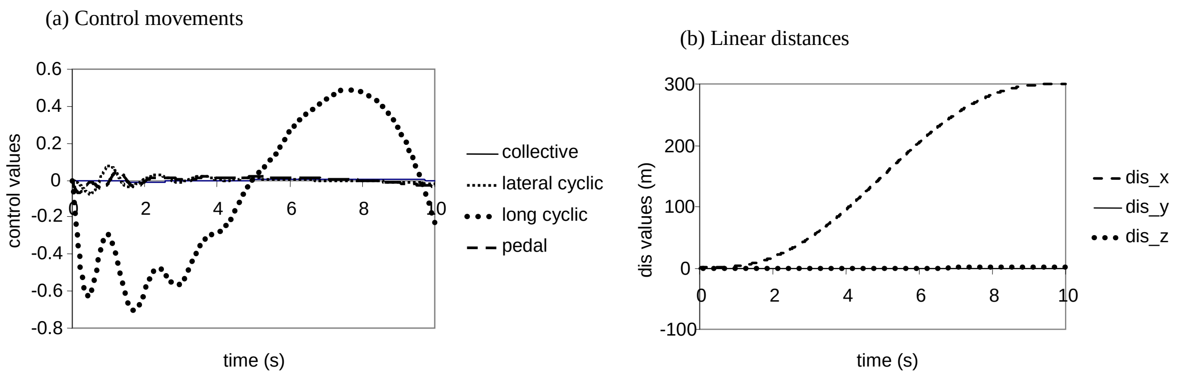
$$f = 1/(1+\max(p_1, p_2, p_3, p_{controls})) \qquad (8)$$

To prevent a dominating effect of one penalty over the others, tolerance factors k_t were introduced, aimed at ensuring that all the penalties are of similar magnitude. This is achieved by multiplying the four penalties by numerical constants k_{t1}, k_{t2}, k_{t3} and k_{t4}, respectively, the figures of which were carefully chosen by series of trial runs to balance all the objectives and eliminate domination, ranging from 1 to 2000, inclusive. The fitness function for the *FourPenaltiesGA* therefore becomes:

$$f = 1/(1+\max(k_{t1}p_1, k_{t2}p_2, k_{t3}p_3, k_{t4}p_{controls}) \qquad (9)$$

RESULTS

A GA was built for Equation 9. In tuning the genetic parameters, Tournament Selection method was used [11], population size of 200, 1-point crossover type of rate 0.9, mutation rate of 0.05, and a maximum of 200 generations, averaged over 30 runs. The controls that produced the highest fitness value were used to test the model, to produce the state and derived variables. The algorithm was tested with 50, 100, 200 and 300 meters target distances. Their results were essentially the same, and served as validation of the novel approach. Due to space constraints, only results for target distance 300 meters are shown in Figure 2.



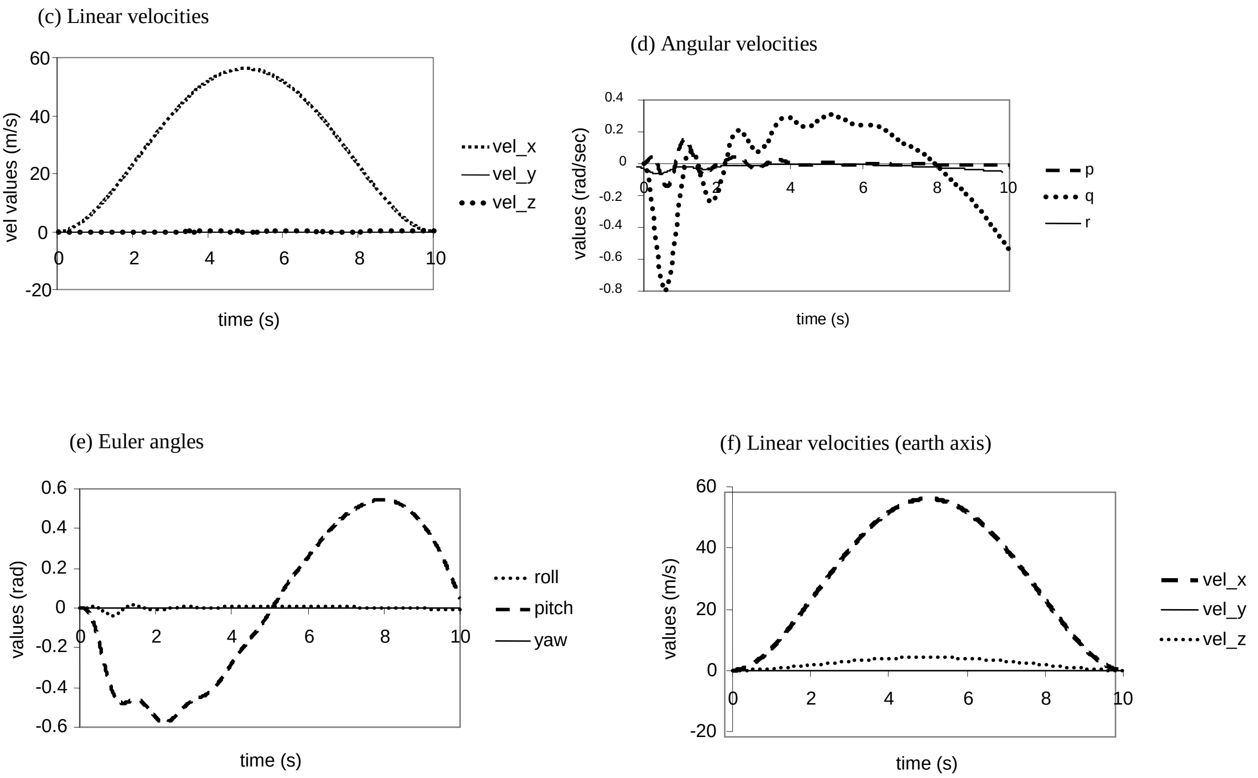


Figure 2: Simulation Results

DISCUSSION

The results reveal the behavioural features of interest of an acceleration/deceleration helicopter flight manoeuvre: symmetrical longitudinal cyclic controls, with the nose tipping down, then up; gradual velocity and acceleration to the maximum, then deceleration at the end of the flight; and flying to the target distance. An evaluation of the developed model pilot is made on the basis of performance and functional efficiency, in terms of what should be achieved in real life. Qualitative and quantitative analysis were used to investigate the human-like nature of the developed pilot and compliance with aircraft design standard.

In the context of this work, human-like means minimising pilot workload while realising the overall aim. Workload plays a very large part in how pilots fly. The GA was built incorporating this objective, where one of the penalties, $p_{controls}$ was aimed at minimising the total controls, and hence reducing pilot's workload. The ability of the model pilot to minimise changes in controls between the present and subsequent time intervals to the greatest minimum, as observed in the plot of control movements, yields human-like behaviour. This prevents the oscillating feature of the control movements.

In flying an acceleration/deceleration manoeuvre, a pilot starts by displacing the cyclic stick forward, causing the nose to pitch down. This results in the increase in airspeed, increased power, and loss of altitude, with the collective control being held constant up till the maximum airspeed [12]. Once the target airspeed is reached, the pilot initiates a deceleration by pulling the cyclic stick backward, reducing the power, while maintaining a constant holding altitude. This causes the nose to pitch up, just before reaching the final stabilized hover. Increasing the collective during this process of maintaining a constant airspeed will make the helicopter to initiate a climb, while decreasing the collective will cause a descent. A good coordination between the collective and cyclic control inputs (up/forward or down/backward respectively), will result in airspeed changing while maintaining a constant altitude.

Performance/functional efficiency evaluation is achieved by means of graphs of control movements, linear distances, linear velocities, angular velocities and pitch attitudes, as shown in Figures 2 (a to f). As shown in Figure 2a, the helicopter is initially pushed nose down to accelerate. It is then pulled up after adjusting to the increasing velocity in the first 3 seconds of acceleration, and after the helicopter has moved to the maximum pitch, it is pushed nose up during the deceleration phase and brought to a hover position. Figure 2b shows that the pilot has successfully flown the helicopter steadily to the target, 300 meters from start along the x-directional axis, in line with penalties p_1 and p_2; starting from hover and ending in hover (Figures 2c and 2f), in line with penalty p_3. The maximum airspeed was attained half way (after 5 seconds), at which point the deceleration began (Figures 2a and 2c). Except for stabilization during the acceleration and deceleration phases, the rotational movements are minimized. As shown in Figure 2e, the pilot achieve a nose-down pitch attitude during the acceleration of about 30 degrees above and below the hover attitude, a constant lateral and heading angles within 0 degrees all through the flight.

The longitudinal acceleration/deceleration manoeuvre forms part of the precisely defined Mission Task Elements (MTEs) that provide a basis for an overall assessment of the aircraft's ability to perform the prescribed tasks, and the results in an assigned level of high quality [13]. According to the standard, the manoeuvre *"starts from a stabilized hover, rapidly increase power to approximately maximum, maintain altitude constant with pitch attitude, and hold collective constant during the acceleration to a maximum airspeed. Upon reaching the target airspeed, initiate a deceleration by aggressively reducing the power and holding altitude constant with pitch attitude. The peak nose-up attitude should occur just before reaching the final stabilized hover, and complete the manoeuvre in a stabilized hover at the end of the course"* [ADS].

The model pilot achieves up to 95% maximum continuous power within 4 seconds from initiation of the manoeuvre (against 3 seconds for adequate performance requirements in ADS), achieved a nose-down pitch attitude during the acceleration of about 30 degrees below the hover attitude (at least 12 degrees for desired performance requirements in ADS); maintained heading within ± 10 degrees (desired performance requirements); achieve a nose-up pitch attitude of 30 degrees during the deceleration phase, before the hover (15-30 degrees for desired performance requirements); maintained an altitude below 15 meters (desired performance requirements), and a lateral track within ± 3 meters (desired performance requirements).

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