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The CSIRO Autonomous Helicopter Project

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Abstract

This paper details the progress to date, toward developing an autonomous helicopter using a scaled size 60 testbed. The discussion includes structural design of landing gear and avionics housing, avionics vibration isolation, visual state estimation, and various linear and neural control modules. Rate gyros and accelerometers have been successfully isolated from rotor and engine vibrations. State estimation using image correspondence techniques has been demonstrated both in simulation and on the real helicopter. Engine governance and linear rate control has been developed and tested. Two neural approaches have also been explored; one has been successfully tested on the actual helicopter, while the other has shown promise in simulation.

1 Introduction

This paper details the development of an unmanned helicopter (UAV) testbed, and the experiments performed toward achieving full autonomous flight. UAVs have recently commanded significant interest in the research community, given their high maneuverability and versatility [10]. These systems can find application in tasks such as 3D Site mapping [11], power line inspection, fire front monitoring and low level surveillance.

Scaled size helicopters pose a particular challenge when compared to their full size counterparts. Characteristic lower damping results in greater instability [10], while small payloads logistically limit sensor types, and more importantly, sensor quality [15]. The fact that many helicopter studies are carried out in simulation can be attributed, in part, to the difficulty in sensing helicopter state. These issues are further exacerbated when using a size 60 (payload ~5kg) over the R50 (payload ~20kg) used by many research groups; the return is a cost saving of around 90%.

Figure 1: Fully Equipped JR Ergo in Flight

A wide range of control methodologies have been applied to small scale helicopters, including linear PD/PID [14, 1], input/output linearization [9], gain scheduling [15], fuzzy control [16, 12], neural control [4, 2], and combinations thereof [8, 13]. Traditional control usually necessitates the development of a plant model, or tedious gain tuning; the required accuracy of these models increases for nonlinear approaches such as linearization feedback. Neural networks, on the other hand, can use learning strategies to avoid the need for a system model. Proving stability, however, can be difficult, and in some applications, the tuning of neural network parameters can be as labourious as tuning PID loops, thus negating their primary advantage. This project will use both types of stategies, such that an unbiased comparison of performance and ease of design may be made, on a common platform.

2 Platform Description

The test vehicle is a JR Ergo scaled size 60 helicopter (height 0.6m, length 1.45m), powered by a single cylinder, 0.5cc, two stroke engine. The aircraft has a main rotor diameter of 1.55m, giving it a lift capability of ~10kg; gross aircraft weight including avionics is ~7.5kg.

Control is maintained using 4 actuators; collecitve pitch δ_{col}, lateral cyclic pitch δ_{lat}, longitudinal cyclic pitch δ_{lon}, and rudder δ_{rudder}. Neglecting cross-couplings, these inputs approximately control vertical acceleration, roll rate, pitch rate, and yaw rate respectively. Throttle would constitue a fifth input if the engine wasn't governed to maintain 650RPM; maintaining a constant RPM simplifies the control problem.

Landing gear is a custom built praying mantis style aluminium frame from which extend fiberglass legs (Figure 2). The aluminium frame makes room beneath the aircrart for the carbon fiber computer housing. Carbon fiber has the advantage of being light, strong, and provides EMI shielding. However, using carbon fiber throughout strongly couples engine and rotor vibrations to the landing legs, inducing a dangerous resonance prior to takeoff. The aluminium frame both damps this resonance and, through deformation, protects the helicopter and computers/avionics during hard landings.

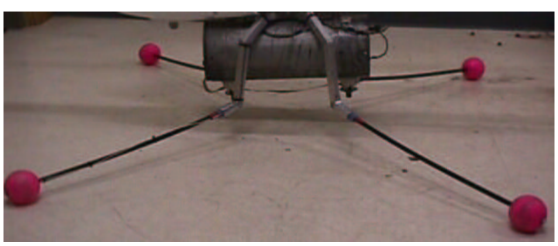


Figure 2: Landing Gear and Computer Housing

The computers include a main control computer (PC104 stack Pentium 233), and a flight computer (dual HC12 board) responsible for system monitoring and signal routing. The sensor suite comprises a GPS, a sonar altimeter, an IMU yielding 3 rates, 3 accelerations, and abosulte roll and pitch, 1 lookahead camera, and stereo vision. The stereo baseline is maximized by mounting the cameras at opposite ends of the computer housing.

3 Sensor Package

The GPS provides position,velocity and heading estimates once a second. The GPS receiver is mounted on the horizontal tail fin, for clearest line of sight to satellites. The sonar altimeter, located beneath the nose, is used to estimate heights of up to 2 meters.

3.1 IMU

The Crossbow IMU uses rate gyros and accelerometers to measure rates about three axes, and accelerations along 3 axes; DSP is used to extract absolute roll and pitch[1]. However, shaker table tests have shown that, when subjected to rotor frequency vibrations, both the rate and acceleration readings are grossly inaccurate; consequently, so to is the attitude estimation.

In order to isolate the unit from these frequencies, the IMU is spring mounted inside the main computer housing. With foam damping included, the isolation has a corner frequency of 6hz. A typical plot of the rates before and after isolation is given in Figure 3.

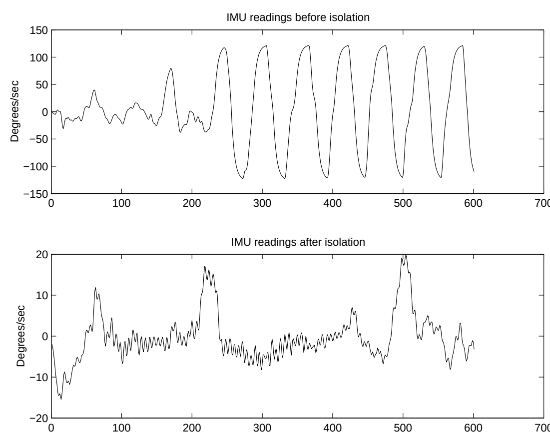


Figure 3: Rate Gyros before and after isolation

Although this stabilises the rates and accelerations, the unit's generic-application Kalman filtering used for attitude estimates is still not reliable. Consequently, a Kalman filter designed for the helicopter application must be used to extract roll and pitch. Combining this with other sources, such as visual state estimation, can further improve reliability.

[1] a custom unit, developed at CSIRO, which is smaller, lighter, and includes a magnetometer, should be in operation within the next couple of weeks

3.2 Visual State Estimation

Integration of accelerometer to find linear velocities will quickly accumulate errors. Differentiating GPS movement provides updates only once a second; furthermore, these are expressed in the inertial frame. State estimation from image flow, on the other hand, yields both linear and rotational velocities expressed in the instantaneous helicopter coordinate system.

Correspondence techniques are used to find image movement between subsequent monocular images. Harris corner detection finds corners in a pair of images, and then zncc matching is used to find point correspondence. While at present a simple radial search space restriction is employed, work is currently being done toward using the previous image movement and epipolar geometry[2] to define the search area.

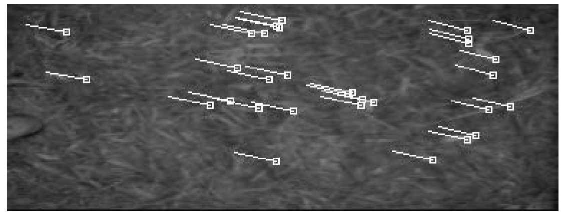
Extracting the 3D rotation and translation from image movement is done using one of 2 algorithms depending on whether the points are coplanar (ground is flat) or in general configuration (ground is irregular). Each algorithm is based on satisfying either the planar or non-planar epipolar constraints [6, 7]. If the coplanar algrothim is used over nonplanar ground, the results become increasingly inaccurate [6]. On the other hand, the nonplanar algorithm degenerates, when used over planar ground [7].

In both cases, the extraction is based on singular value decomposition. Consequently, there are several solutions that satisfy the epipolar constraints. These can be disambiguated by exploiting the fact that the camera on a helicopter can only see what is in front of it (positive depth constraint). Furthmore, the diagonal elelements of the SVDs can be used to determine whether or not the ground is planar. Translations are given only up to a scale determined by height. Successful height estimation using the stereo vision has been previously detailed in [5]. A full description of the two algorithms can be found in [3][3].

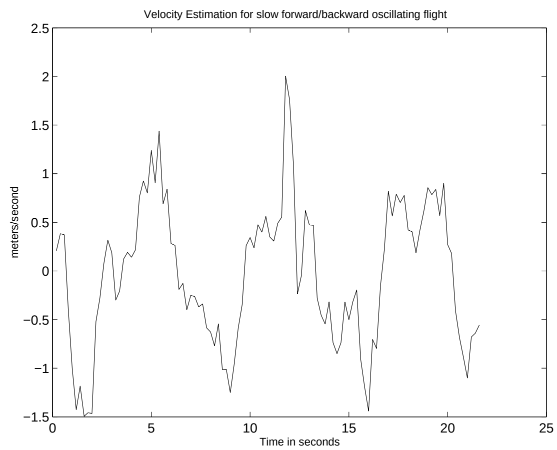
Both the planar and nonplanar algorithms have been successfully tested on simulated image points detected in a computer generated environment. Real helicopter tests have thus far been conducted over planar ground only. A plot of velocities extracted during a slow oscillatory forward/backward flight (Figure 4) illustrates that the results thus far are promising; more comprehensive testing continues.

[2]Epiplar geometry constrains where points in one image frame will appear in another image frame translate and rotated by T and R.

[3]Obtainable by email



(a) Sample image movement detection



(b) Velocity Estimation for a slowly oscillating forward/backward flight

Figure 4: Velocities extracted from images during forward flight

4 Linear Control

Four linear controllers have been developed to maintain engine RPM, yaw rate, roll rate and pitch rate.

4.1 Engine Governor

Engine speed is maintained at 650 RPM; this figure was determined by looking at engine speed during piloted, hover-envelope flights. A PI controller using feedback from a hall effect RPM sensor generates throttle demands. A feedforward term from the collective pitch is also included to compensate for the extra loading experienced by the engine as collective pitch is increased (Figure 5). All gains were determined experimentally; the choice of gains was not found to be overly critical. Engine speed error was within ± 30 RPM; this is actually the resolution limitation of the sensor.

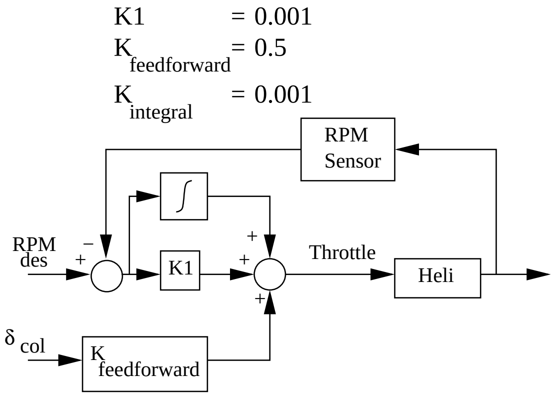


Figure 5: Engine Governor

4.2 Yaw Rate Control

While a rate gyro augmentation system is already fitted to the helicopter, information regarding its exact internal workings is unavailable. Consequently, a yaw rate stabilisation loop has been developed regardless. PI control using yaw rate feedback from the IMU outputs demands to the rudder servo (Figure 6). While the rudder essentially commands yaw rate, the integral term is necessary to find the zero rate setpoint required to counter the main rotor touque.

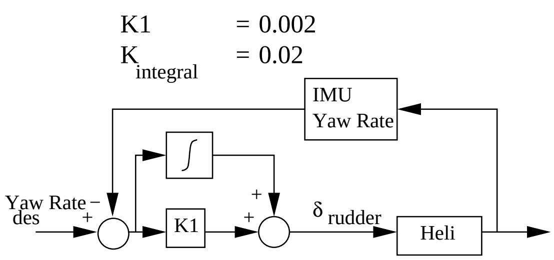


Figure 6: Yaw Rate PI Control

4.3 Attitude Rate Control

Roll and pitch rate control is maintained using simple proportional controllers (Figure 7). Feedback is again provided by the IMU. Due to the pendulum nature of the helicopter loaded with avionics, zeroing the rates has the effect of also stabilising the attitude. In effect, the rate control is damping the higher frequency rotations, while the low c.o.g. provides attitude feedback. Nevertheless, attitude control will need to be developed as the next step toward closing the velocity loops.

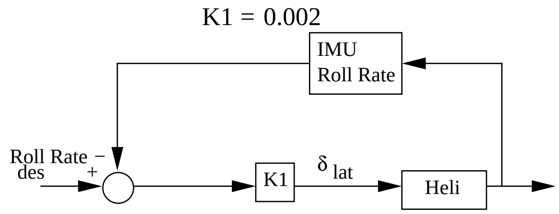


Figure 7: Attidue Rate Control

5 Neural Control

Two types of neural control are being explored. The first, direct Behavioural implementation, indescriminantly uses flight data generated during a stable hover to try and mimic pilot actions. This concept would then be extended to teach forward flight, on the spot turns etc. The second method is more modular and more descriminatory in how it uses the data. One module is an inverse rate controller developed using general flight data, while a second module learns to send rate commands based on velocity and attitude errors.

5.1 Direct Behavioural Implemenation

In this method, the pilot flies in a desired manner, while the NN learns (using supervised learning) to mimic the pilot actions. This method has been shown to maintain stable hover flight for around 15 seconds; full details are given in [4]. However, close analysis of the weights, and the controller's responses to particular offline sensor step inputs has revealed that the network commands can often be nonsensical, and more importantly, destabilising. This can be attributed, in part, to poor generation of data which effectively represents the task to be mimicked. In particular, small destabilising pilot inputs coupled with a strong association (dynamically) between rates and control inputs, leads to a network that finds destabilising associations between rates and control signals. The latter is exploited in the modular design.

5.2 Modular Neural Control

The strong dynamic association between control inputs and resulting rates, can be exploited in order to develop (using supervised learning) an inverse, feedforward, rate controller. A comparison of the inverse NN rate controller output (lateral cyclic) to actual pilot control signal (lateral cyclic) data logged during a piloted flight is given in Figure 9. Since much of the dynamic cross-coupling exists at this

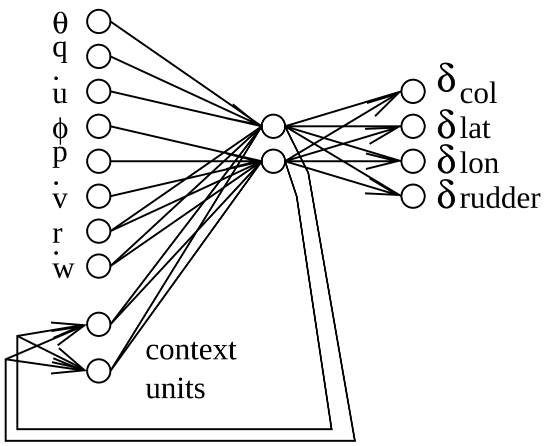


Figure 8: Direct Behavioural Implementation

level, such a controller can provide a decoupled interface for a higher level, adaptive feedback controller.

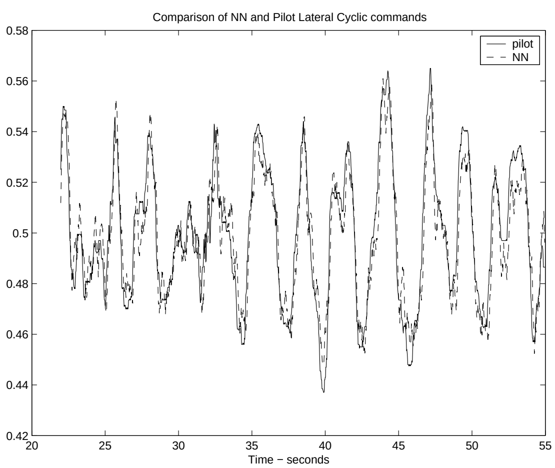


Figure 9: Comparison fo Pilot and NN Control Signals to Produce Desired Angular Rate

This feedback control is performed by another neural network. A combination of reinforcement learning and supervised learning is used. Reinforcement learning has the advantage of enabling online learning (via cost function minimization) throughout the lifetime of the controller. One of the disadvantages is that it is often slow to converge. Supervised learning from the pilot is used to help expedite convergence during the early stages of learning. However, pilot data is only used when the pilot is deemed to be acting appropriately; this decision is made using the reinforcement cost criterion. Simulation results for this method have shown that a simple neural network can learn and maintain control in real time.

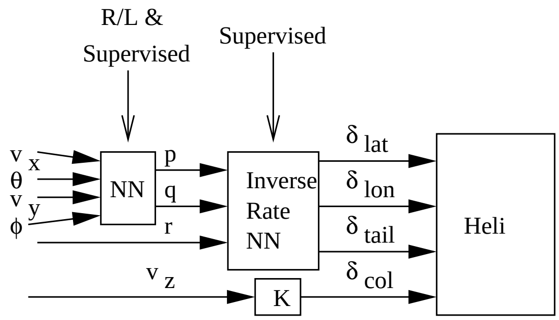


Figure 10: Modular NN Implementation

6 Conclusions

This paper describes the current status of the CSIRO autonomous helicopter. The IMU has been successfully isolated from vibrations, resulting in useful rate and acceleration estimates. Vision algorithms have been implemented to extract rotational and translation velocities from real flight images. Linear rate control has been successfully applied. Two forms of neural network control have also been tested (one on the helicopter, the other in simulation) with some success.

The next step is to integrate the visual and IMU estimates into a unified sensor suite. Following this integration, attitude and velocity loops will be closed using linear control methods. The second neural approach (thus far tested in simulation) will also then be experimentally tested.

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