PILOT WORKLOAD ASSESSMENT USING FLIGHT SIMULATION

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Abstract

A vital aspect of aircraft acceptability is its ability to operate under extreme conditions without requiring an excessive pilot workload. In recent years, the ability to predict this somewhat esoteric quantity using computational techniques has been pursued. Apart from enabling these tasks to be carried out with improved efficiency and safety, it has also provided the ability to perform tasks under tightly controlled flight conditions. This is of major importance to operation in severe atmospheric conditions where flight in proximity to vertical surfaces is common.

Rapidly increasing computing power has allowed flight simulation to become available at increasingly modest costs. Consequently, the capability to examine the performance of an aircraft in relation to the corresponding pilot workload can be realistically achieved at an early stage of the design. The research to be described in this paper comprises an investigation into using such low cost simulation software and combining it with advanced processing techniques to arrive at a method of quickly estimating pilot workload and thereby rapidly assessing the implications of design modifications.

The method described records the lateral and longitudinal control stick inputs the pilot makes to perform an aircraft manoeuvre for a variety of flight conditions and handling qualities. This process inevitably produces large amount of data which will require efficient processing. In order to achieve this, the data is then smoothed and reduced using Fourier and wavelet analysis technique. It was considered that conversion of these results to a workload rating would be an ideal candidate for a neural network, due to the fuzzy and subjective nature of this assessment. This neural network is trained with the results obtained from the signal breakdown as inputs and the pilot's assessment of workload as the target output. This process is validated by presenting previously unseen data to the network and continuing the training until suitably accurate workload ratings are predicted, resulting in a system capable of measuring workload given just control inputs.

The advantages of this method over existing methods relying on direct pilot feedback are clear. Workload can be estimated at an early stage of the design process using simulator software, and responses to changes given almost instantly using a real-time display of workload. The novel use of a neural network makes the method adaptive to changes, and the ability to function correctly with a variety of aircraft and pilots without requiring fundamental changes to the algorithm, or any in-depth technical knowledge of this research.

The study has shown promise, in that it corresponds well with the Bedford rating given by the pilot, and it therefore warrants further investigation.

Nomenclature

CSD	Control Stick Displacement
FS2002	Flight Simulator 2002
WR	Workload Rating
ms	milli-second
E_i	Neuron output layer error
w_{ij}	Error gradient
out_i	Sigmoid function output

Introduction

Many different definitions of workload exist, for both pilots and system operators in general. Many of these definitions are conflicting, and some reports give no definition at all. For example, Federal Aviation Regulation (FAR) 25 lays out requirements for crew workload, and is a legal constraint for airworthiness certification. It uses such phrases as “analysing and demonstrating workload” and “the workload on individual crew members”, yet it offers no definition of what workload actually is, or how it should be measured. Some definitions are based on time concepts, where the workload is evaluated as the time required to complete a task over the time available to complete it [1]. Others are far more complex and psychological in nature, centered on the cognitive capacity of the operator, namely the pilot. For engineering purposes it is important to have an exact definition. Unfortunately, “*there is no empirical technique for proving a definition”*, and indeed *“when the human enters the equation we do well to avoid a foolish search for precision where none exists*” [2]. For the purpose of this report, workload is considered based on the general definition by Kantowitz [3], phrased in Parasurman & Mouloua [4] as:

“*Pilot workload is defined as an intervening variable, similar to attention, that modulates or indexes the tuning between the demands of the environment and the capacity of the operator. As an intervening variable, workload cannot be directly evaluated or observed. Instead, it is a conceptual, multifaceted construct that must be inferred from changes in observable data*”

Workload Influences

The consequence of recent advances in aircraft performance and avionics has been an explosion in the complexity and sheer quantity of information that is available to today’s pilot. This has resulted in a dramatic increase in the pace of flight operations and reducing the pilot’s available processing and decision time [5]. Workload, it would appear, can only increase without positive steps being taken to control it.

The workload experienced by a pilot during flight consists of many different tasks. These may include:

- Instrument monitoring
- Lookout (scanning the local airspace for traffic)
- Applying control inputs to move the cockpit inceptors
- Solving problems and planning tasks ahead
- Communicating with crew, air traffic control or other pilots
- Weapons control as well as dealing with enemy threat.

Many factors can influence the degree to which these tasks affect the overall workload. They may be grouped into categories such as:

- **Pilot:** This includes pilot’s skills and experience in assessing flight situations as well as cognitive capacity
- **Aircraft:** Its capabilities and ease of flying
- **Internal Environment:** This includes atmospheric conditions, cockpit layout and level of system autonomy
- **Crew:** The number of flight crew on board
- **External Environment:** This includes meteorological conditions and other flight traffic
- **Task:** The difficulty or complexity of the manoeuvre being flown.

<u>Motivation</u> Peak pilot performance occurs at an intermediate level of workload, see Figure 1. Too low a workload level results in the pilot becoming complacent with the situation. Complacency in the cockpit is certainly not desirable, as it can lead to fundamental errors being made. On the opposite end of the curve, the pilot becomes overloaded with work, and cannot maintain the level of performance required for safe operation. Once the peak is passed, performance drops rapidly with increasing workload, which again is highly undesirable. During the intermediate stages, the pilot performance increases with workload. Effectively, the pilot ‘tries harder’ as the situation demands, and as a result actually performs better. The optimum operating

condition occurs just below the peak, thus allowing a small safety margin for unexpected events.

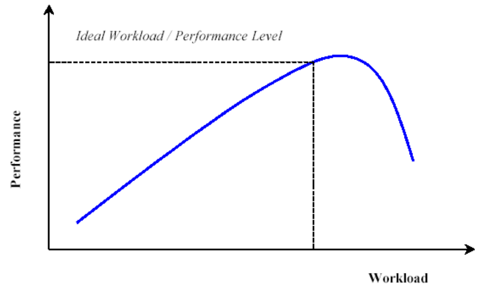

Figure 1: Pilot Performance Shown Against Imposed Workload

The level of workload imposed on a pilot is therefore an important consideration. It has an influence on many design and operational areas, this includes:

Safety: Optimising pilot workload means optimising pilot performance, thus reducing the likelihood of a pilot making errors. From the above discussion, extremes of workload should be avoided.

Crew Size: The level of workload anticipated in a given situation can determine the minimum crew size required on an aircraft. A lower workload environment allows smaller crew sizes, thus reducing operating costs.

Automation: Technological advances in cockpit and avionics design has significantly reduced the level of workload experienced by the pilot during flight. Some researches now express concern that aircraft are becoming over-automated, thus slipping too far back down the curve shown in Figure 1.

Operating Procedures: are scrutinised for their effect on pilot workload, and many are regularly revised to maintain an acceptable level. Operational limits of aircraft may also be set by the workload on the crew, as quite often in aviation the human becomes the weakest link in the chain.

Certification: In an effort to provide a safer working environment in flight operations, pilot workload is becoming an increasingly important design parameter. It is imperative that the workload levels experienced at the extremes of the flight envelope are within acceptable limits, as prescribed by flight regulatory authorities. As described in FAR 25 and similar publications, satisfactory pilot workload is now a requirement when certifying aircraft for flight operations. In order to achieve an optimum level of performance in a safe environment, there is first a requirement to be able to measure the workload on the pilot. Simulation has emerged as a reliable and low-cost approach to achieving this aim. Assessing pilot workload using desktop software will reduce the dependency on costly, and potentially dangerous piloted evaluations. There is a strong motivation for developing a reliable and low cost method of workload assessment that can be implemented on such simulators.

Workload Assessment

Initial research hasled to three different approaches to workload assessment, that of analysing the direct pilot control input, a secondary task method looking a measuring the pilot mental spare capacity, and a physiological heart rate based assessment [6]. It was decided that the analysis of direct pilot input was more fruitful since it not only reflects the pilot state and control strategy but the simulator validity as well. A secondary task measurement was also implemented in order to assist the test pilot in providing a subjective workload rating (WR), see Figure 2.

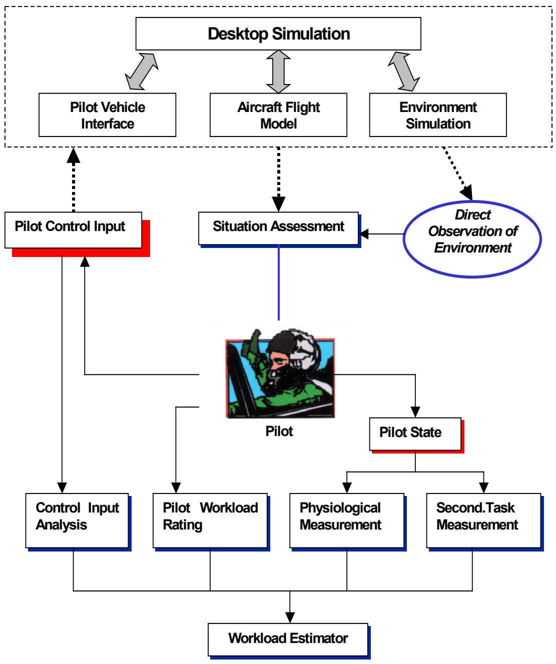

Figure 2: Workload Estimation Block Diagram Architecture for Desktop Simulation

The hypothesis made in this study is that the measurement of pilot induced control inputs during flight operations contains sufficient information for workload to be assessed accurately [7]. By investigation of signal analysis techniques such as Fourier and wavelet transforms, an attempt is made to screen the raw data for any residual features that may depict a certain level of workload. In particular, effort is focused on frequency domain breakdown to collect the important features in the stick input signal.

Once these features are recognised, it will be possible to train the neural network algorithm to associate them to a collected set of quantified workload ratings awarded by the pilot upon task completion.

The neural network developed is a mathematical construct that consists of layers of nodes, and connections between nodes called links. It attempts to model the data processing ability of the human brain as we understand it, which consists of biological neurons connected by synapses. Each neuron in the network has an activation that determines its output, and each synapse connecting two neurons has a weighting that determines the importance paid to the connection. In conjunction with simple mathematical functions such as multiplication and summation, this model makes it possible to build a complex pattern recognition system, given the correct setting of the weights between neurons. There are several reasons for the decision to use a neural network to analyse the Fourier and wavelet data. Alternative techniques include examining the frequency response data by hand and attempting to pick out guides to workload, then automating this procedure; or using a rule induction method whereby important transient elements from the wavelet transform are analysed. Although a neural network algorithm is complex to implement, once successful, training of the network and analysis of new signals is automated and needs only minor further input from a human operator. The network has the ability to learn extremely complex relationships between data that is not obvious by human inspection, or hidden too deeply in the data to become apparent with the simple two-option structure that decision trees produced by rule induction rely upon. In addition, once trained and tested, it is possible to add new data (such as how a new pilot handles the controls) and retrain the network in-situ to improve the accuracy of the results generated.

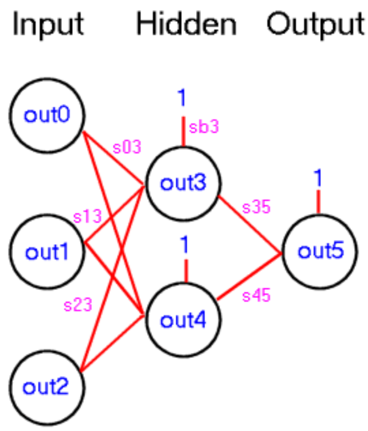

Figure 3: Layers, connecting synapses and neuron biases

Neural Network Approach

<u>The Back-Propogation Neural Network</u>

Figure 3 shows a simple network consisting of three layers, which by convention are labelled the input, hidden and output layer. The input layer neurons represent the input pattern that is supplied to the network when training or performing a calculation. The hidden layer neurons use the outputs from the input layer in conjunction with the weight of the connecting synapses to calculate their own activation, and in turn pass this onto the output layer through another set of weighted synapses. The result is a complex mathematical relationship between the activation of the output layer neurons, and the activation of the input layer neurons, and it is from this starting point that pattern recognition is achieved. When a network is first created, the synapse weightings to give the correct relationship between input and output patterns are unknown. For the network to be useful, there must exist some method of calculating these correct weightings. The algorithm chosen to do this is the ‘back-propogation method for a feed-forward multiple layered neural network’ outlined in [8] and [9]. The three-stage procedure for training the network is:

• Initialise the network topology and assign small random weights to all synapses.

• Present the network with a training pattern. This consists of an array of input values to be fed into the network, and an array of the desired target values that the network should generate. Calculate the network output by performing a forward pass through the network.
• Determine the error between the actual network output, and the desired target output. Use this error to modify the weighting of the synapses to minimize it, using a gradient descent where error is propagated backwards through the network. Repeat for different training patterns until an overall low error state is achieved.

Forward Pass Calculation The forward pass through the neural network is used to calculate the activation of the output layer neurons. Starting from the input layer neurons, the activation of each hidden layer neuron is calculated by summing for each input neuron the product of its output by the synapse connecting the two. A bias is then added (a bias can be considered a neuron with a constant activation of 1.0), and the sigmoid transfer function converts this final summation into a bounded output. The sigmoid function is continuous and non-linear, with a definable spread; a critical feature to ensure that error is propagated backwards correctly [9]. This process is then repeated in a similar manner from the hidden to the output layer to arrive at an output.

Backward Pass (Training) The backward pass is used to adjust synapse weights once the difference between the target output, and the actual output have been calculated. It can be thought of as calculating the gradient of the error surface for every output neuron with respect to every hidden neuron, and using this to determine the adjustment that needs to be made to minimise error.

$$E_j = \sum_{j=1}^{Nout} \left(spread \times out_j \times (1 - out_j) \times (target_j - out_j) \right)^2$$

Equation 1

$$E_i = spread \times out_i \times (1 - out_i) \times \sum_{j=0}^{Nout} E_j w_{ij}$$

Equation 2

Once the error associated with each neuron in the output layer has been calculated (using Equation 1), the error can be propagated backwards to the hidden layer using the synapse weightings between the two layers to assign 'blame' for the error (using Equation 2). Finally, after all the error gradients for each hidden and output neuron are known, the error can be minimised for each neuron by following the gradient using Equation 3:

$$w_{ij} = gain \times E_j \times out_i + momentum \times w_{ij}$$

Equation 3

A gain is used to allow the 'step-size' taken to be altered in order to avoid overshooting. A variable momentum term can also be used to store the previous gain adjustment, to attempt to prevent descent into local minima. The network is considered trained when the error associated with each training pattern is acceptably low, which for the purposes of this application will be generating a rating that agrees with the target rating to the nearest WR.

Secondary Task Assessment

Background Theory The concept of secondary task testing involves giving the pilot a side task to complete, separate from that of the flying task (or primary task). In general, secondary task performance decreases as workload on the pilot increases. Secondary task methods have been, and still are, used in the simulated cockpit to measure pilot workload. In almost all of these cases, a strong correlation was found between secondary task performance and task difficulty or pilot stress level [10]. Therefore, it is possible to identify the workload level on the pilot from their secondary task performance [11] [12].
Effect of workload on Secondary Task
Workload can be assumed to affect the pilot's secondary task performance in four ways:
•The pilot can become completely immersed in the flying task, such that their senses are devoted entirely to the flight. They may filter out all other external stimuli, and therefore 'not hear' or 'see' the secondary task.
• The pilot will prioritise the tasks during the flight test, with the secondary task, by definition, being the lowest priority. Thus,

even though the pilot is aware of the task, he/she is unable to divert from the flying task to respond to it.

• Once the pilot has devoted a time segment to the secondary task, their performance on the task may be impaired due to the pressure on them to carry out the task quickly, leading to mistakes.

• In the final phase, the response must be entered correctly. Again, this may be impaired by time pressure on the pilot, causing them to strike the wrong key/button.

Normalising the Results Repeating a test with a different pilot would result in a different workload rating, as the ability and technique of each pilot will be different. Hence, there is a requirement to log the pilot's natural capacities (reaction time, musical perception, time perception, ball counting etc) to provide a baseline comparison, otherwise the workload rating given may be dependant on the mental arithmetic ability of the pilot. If these baseline conditions are factored into the workload calculation correctly, the result is a workload rating independent of the pilot, thus allowing comparison on a universal scale.

Implementation It was decided that the tasks would be implemented using computer software to display and log all information. This eliminates the need for a human to perform any actions or record results during the test. The computer program could be designed to run either on an adjacent platform, or on the same platform as the flight simulator. The first is the simpler method to implement, but has the obvious disadvantage of requiring extra hardware and space within the 'cockpit' area to set up this equipment. This approach necessitates the pilot to divert their visual attention from the main flying displays, and in doing so makes a clear distinction between primary and secondary tasks. Care must be taken however to ensure that this does not cause a drop in performance of the flying task, or the workload that is being measured would be affected. By using a laptop computer, it may be possible to complete the testing in a real aircraft, depending on the aircraft in question and associated safety issues. This would highlight the difference between the simulator ratings and those in the real aircraft. Similarly, the testing could take place in different simulators. The second set-up is immediately made more complicated by the need to integrate the secondary task into the simulation software. Either the program code would have to be compatible with *Microsoft flight Simulator 2002* (FS2002), or a separate program window would be displayed on top of the FS2002 window. This would have to accept inputs without taking the window focus away from the flight simulator. From a technical viewpoint, both programs share processor time in addition to other system resources. If too complex, the secondary task program could affect the performance of the flight simulator software. The main advantage of a program running as part of the flight simulator is that the entire flight-testing procedure can be conducted within one package. The above arguments are extensive and demonstrate the complex choice between the two options. They each pose their own technical and practical difficulties, in addition to the effect on the workload being measured, which must also be taken into account. Based on the above discussion and the nature of the tasks, the decision was made to implement the mental arithmetic secondary task as a separate program run on a second computer platform. This allows for an extensive and self-contained program, with the ability to store collected data and process it at a later stage without the need for FS2002 to be running.

Testing Procedure

Simulator Setup The flight simulator set up used for the purpose of this study is shown in Figure 4. The pilot sits in one of two Harrier ejector seats. One is equipped with Saitek X36 flight stick and throttle, plus Thrustmaster Elite rudder pedals. The other is equipped with a customised Cyborg 3D stick and custom made collective and pedals, which are set up in a helicopter configuration. The two seats are side by side and mounted on a plinth, with the left hand side seat used for fixed wing testing and the right hand side seat for helicopter flight.

In front of the pilot is a monitor, which will display the control panel for the appropriate aircraft flown. The main view is projected onto a white wall via a Toshiba TLP710E projector.

For the fixed wing seat, the stick is mounted on a hinged shaft to allow easy axis to the seat and to let the stick rest in the correct flying position. The throttle is mounted on a wooden upright - which is set at a comfortable position for use.

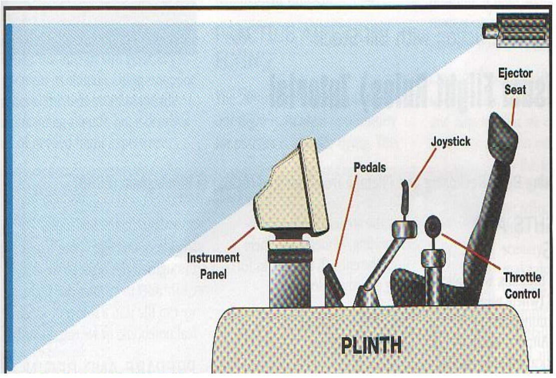

Figure 4: Flight Simulator set-up [13]

To the left of the pilot is a keyboard and mouse, used to control aircraft activities (landing gear, fuel pumps, flaps etc), and operate other features of the simulator.

Using FS2002 as the driving simulation software, it was possible to set up a series tests for the pilot to perform. These consisted of maintaining heading/altitude tests, as well as slalom tests. To ensure that a wide range of workload is experimented by the pilot, the level of difficulty of these tests was varied by adding different turbulence levels during flight. Slalom tests are made more difficult by reducing the distance between the slalom posts.

A secondary task running parallel to the primary flying task is set up on laptop independent of the main simulator system. The secondary task consists of simple set of arithmetic operations that the pilot has to perform. The secondary task is a measure of the pilot spare capacity and hence the level of workload experienced. The secondary task is merely there to assist the pilot in providing a subjective workload rating using the Bedford scale shown in Figure 5.

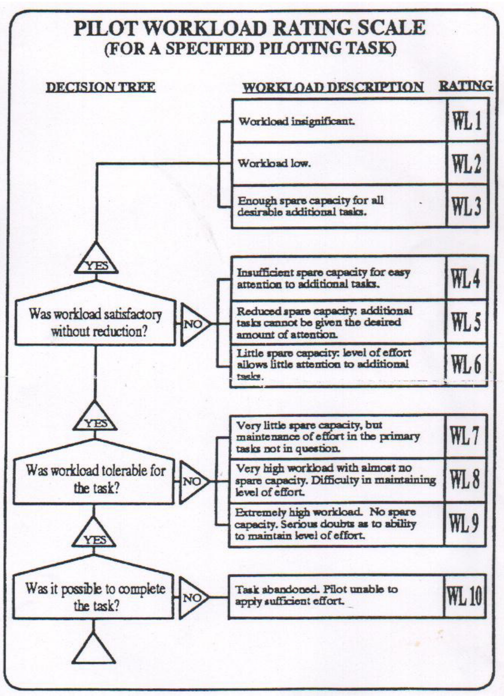

Figure 5: The Bedford Scale

Implementation

After discovering there was no software that would record the raw input control deflections that the pilot produces while flying the aircraft the Flight Control Logger was developed Figure 6.The logger makes use of the DirectInput API released with DirectX 8.0, and so requires this version or later of the DirectX runtimes to be installed to operate. A sample of the logged data from the maintain heading and altitude test is shown in Figure A.1 - see appendix.

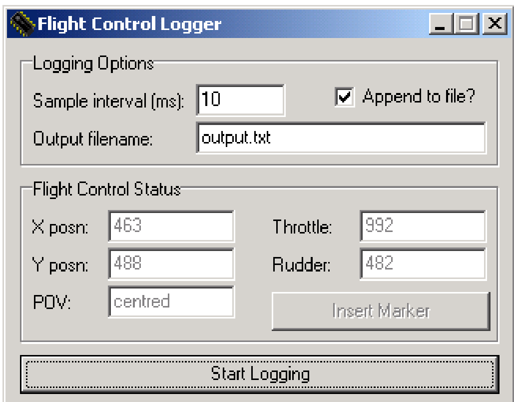

Figure 6: The Flight Control Logger window

At a 10ms sampling rate a Fourier transform was applied to produce a frequency response for each 10 second segment of a single test.
Data inspection showed that above 10Hz the response was a constant intensity noise no matter what test data was presented. Additionally, it was reasoned that no human could produce control frequencies higher than 10Hz. Figure 7.

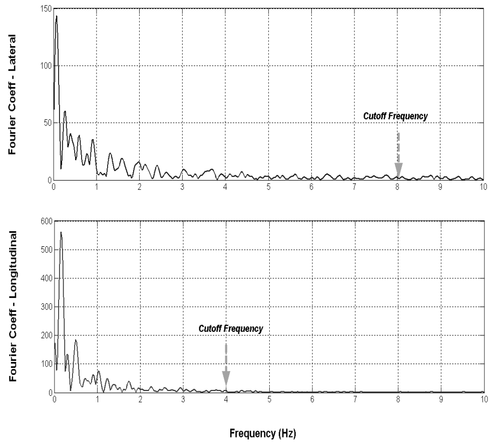

Figure 7: Up/down slalom Low difficulty. Frequency Spectrum. 10 sec sample

In some test segments the amplitude associated with certain frequencies was very high, creating a sharp spike in the response. This response needed to be normalised to give a range of amplitudes between 0.0 and 1.0. A problem would arise if this data were to be fed into the network keeping the highest spike from all the tests as 1.0, since the rest of the signal would be drowned out. It was therefore decided that any spikes with an amplitude higher than 200 would be clipped to 200, preserving the importance and accuracy of lower intensity frequencies. After this clipping, the 1000 frequency amplitudes each for longitudinal and lateral were written as bytes to a binary file ready for import into the neural network, where 0x00 represented an amplitude of 0, and 0xff represented an amplitude of 200 or greater.
As for the wavelet transform, the scale was varied logarithmically, whereas the position shift in time was calculated on a linear basis according to the desired resolution. Jones *et al* [14] suggest that for the purpose of Control Stick Displacement (CSD) analysis, the analyzing wavelet can be chosen in the form of a pulse. With this choice much of the information concerning the structure of the data is concentrated in the local minima and maxima of the correlation surface. In particular, the signal can be reconstructed as a discrete sum of pulse shaped features, whose position and scale are matched to those of the local extremes. A mother wavelet with the shape of a pulse was used for the calculation of correlation surfaces in this study. Upon calculation of the correlation surfaces for each test data, the local maxima and minima were located and translated into a binary input to the neural network. Figure A.2, see appendix.

Using the developed software the neural network was configured as shown in Figure 8. The number of input neurons was set to the number of bytes in the input files (1000 each for the Fourier transform of the x and y stick movement). The number of output neurons was set to 1, giving a single output between 0.0 and 1.0, which will be a representation of the workload rating. The hidden layer neurons, which could number anywhere between 1 and 2000, were set from experience at 1500. If training was slow or failed to converge, this number could be decreased or increased as needed.

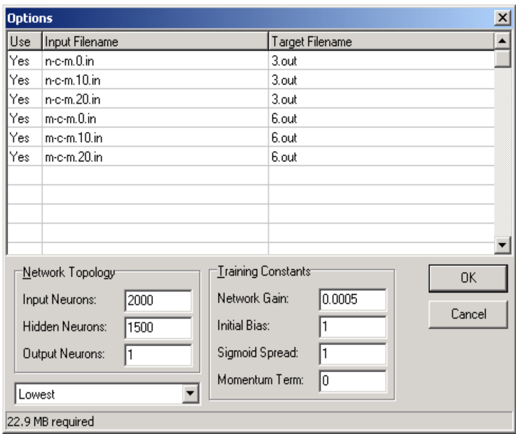

Figure 8: Initial configuration of network parameters

Results

Network Training: The network was given 10 second segment patterns of frequency spectrums for a maintain heading and altitude tests, with flight conditions ranging from none, light, moderate, to severe turbulence.

The network has been able to differentiate between these four input signals, and hence different pilot control inputs, shows that the information needed to determine pilot workload is present in the data presented to it, see Table 1 in appendix. In other words, a frequency response generated from a Fourier transform is enough, in this case, to provide an indication of pilot workload, for the task of maintaining heading and altitude described.

It was found that input patterns in the frequency spectrum were ideally suited for recognition by a neural network, since the underlying algorithms of the network, based on summation of inputs (which is analogous to integration) and multiplication or division by constant values (analogous to taking an average). In addition, the network has the capability to automatically screen out regions of the frequency spectrum which are not relevant (for example, noise, or random data) which is advantageous to automatic processing of human data for signal analysis.

Verification With Unseen Data: To verify the ability of the network to obtain further estimation of workload it is necessary to input unseen data and to check the workload rating it produces is correct.

This time the network is initially trained with 5 seconds signal patterns breakdown for a maintain heading and altitude test. Table 2, see appendix.

All workload ratings for light, moderate and severe turbulence are correctly estimated to 1 WR. Yet again the network shows good convergence when trained. Table 3, see appendix.

Because a figure is needed for pilot estimated workload, it is necessary to use data from the flight tests conducted, since there is no other way to generate a figure for workload. However, the actual data that will be used to test the network will not have been used to train it, and so it can be considered unseen, even though it is from the same flight test.

Although there is more variation in the individual workload ratings generated by the network for this unseen data, the average at the end agrees closely to the pilot predicted workload, in each case giving the correct WR. This suggests that if many control stick samples are taken from a task and the results averaged over time, the neural network would be able to provide a good estimate of workload.

The network was next set up to attempt to learn a workload relationship between the different control patterns in the up-down slalom tests. The four tests used were two up-down slaloms of different difficulties, in both the zero turbulence and light turbulence conditions seen in the maintain heading and altitude tests earlier. See table 4, appendix.

In this case, the error associated with the light turbulence up-down slalom 1 training patterns were all much higher than the average, and gave higher workload readings than the test pilot indicated, however, in absolute terms the error is low because the network as a whole has converged well.

Further analysis of the frequency spectrum suggested that when a turbulence element is added to the overall workload estimation process, the difference between frequency responses can no longer be isolated as being caused by either increasing difficulty of maneouvre, or increasing difficulty of aircraft handling alone. They are in some way coupled, as the pilot attempts to perform the more complex maneuvre while correcting for turbulence at the same time. This will have a tendency to associate one single workload value with more than one set of control stick frequencies.

Thus, the training from these initial patterns has been successful with Fourier analysis, and the foundation of a system for calculating pilot workload from analysis of control stick data is proven.

As for the wavelet analysis the maintain heading and altitude test was used, in which all four turbulence conditions were included in the network training programme, as shown in Table 5. Looking at the WR ratings calculated for the zero and the light turbulence conditions shows that the network is unable to distinguish between these input patterns, and has hence reached an average value between the two, which it produces every time either pattern is given to it. In order to verify this result, it was decided to retrain the network with zero and light turbulence being assigned a WR of 3, and moderate and severe turbulence a WR of 6, and to check if the network can tell them apart. The results from this training run are shown in the Table 6. This seems to suggest that when presented this particular wavelet data, some workload information is being lost, and only a rough estimate of workload is possible.

Conclusion: The signal analysis of the stick data has highlighted the important features in the signal. The neural network effectively learned the combinations necessary for specific workload ratings and achieved good accuracy. It was shown that for the tests used, the Fourier analysis was more accurate than the wavelet analysis. The neural network is only able to provide accurate estimations of pilot workload when that workload depends on a single variable. Coupled situations in which workload depends on factors such as turbulence and difficulty of manoeuvre at once are problematic to train, and yield less accurate results due to an interference between the frequencies generated from a Fourier transform. When trained with enough data, where a single variable is altered to induce workload changes, the neural network is able, in conjunction with an average taken over time, to provide an estimate of workload rating from unseen but similar data that is accurate to within 1 WR.
The flight simulator used for flight testing was shown to be adequate for the task. No significant effects on workload caused by deficiencies in the simulator level of realism were observed.

Recommendations

Application of better redundancy methods and filtering techniques should improve considerably the selection of important features in the signal allowing a faster and more efficient training of the neural network. Further calibration and testing would allow the neural network to be better trained, thus increasing its accuracy. Detailed studies are also needed to deal with the complex input patterns.
As for wavelet analysis technique used, a more accurate features selection can be performed by using redundancy techniques such as weighted sum of residuals and orthogonalisation, whereby a rigorous selection of local extremum in the correlation surface is achieved. This might enable the neural network to recognise and lock faster into a solution and identify differentiating patterns in input signal associated with different workload ratings.
Although training a network is a time and data-handling intensive process, calculation of workload using an already trained network only requires a Fourier transform and simple forward pass. This should be able to be achieved faster than the time period over which data is collected, leading to the goal of a real-time workload monitor being achievable.

Finally, the examples discussed have only considered the influence of primary control activity on workload. The techniques could be extended to include the effect of secondary compensatory inputs in other axes, or to cases where two or more axes of control have primary role.

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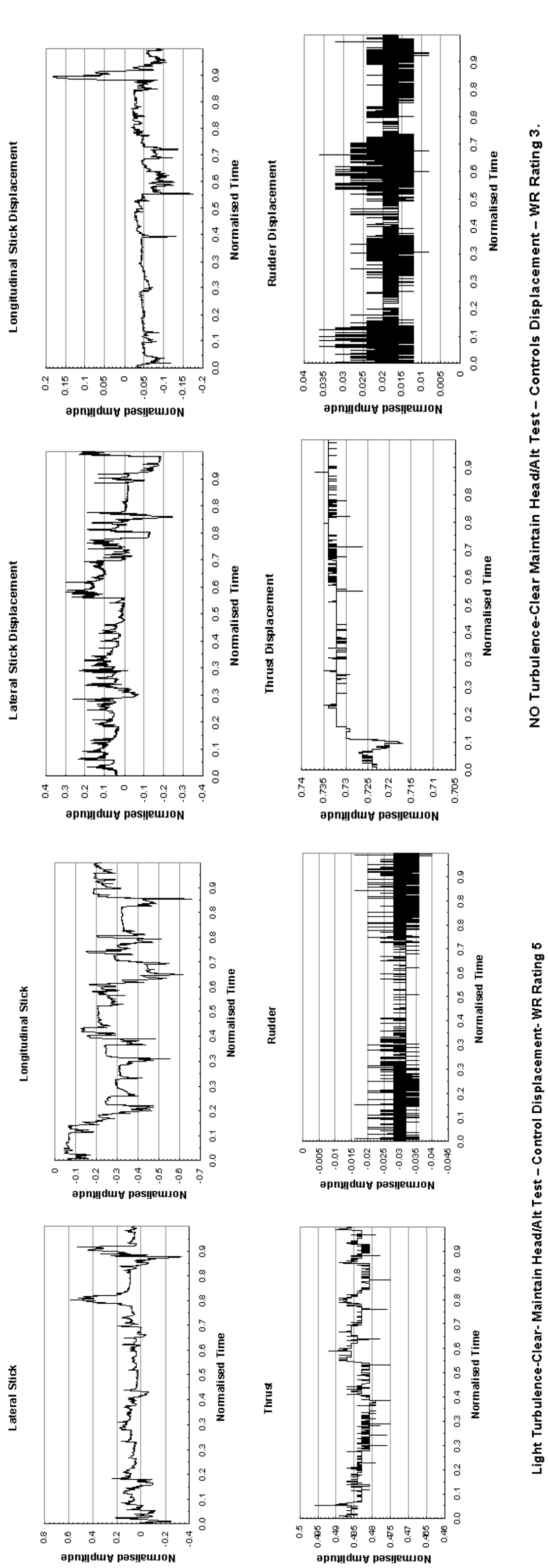
APPENDIX



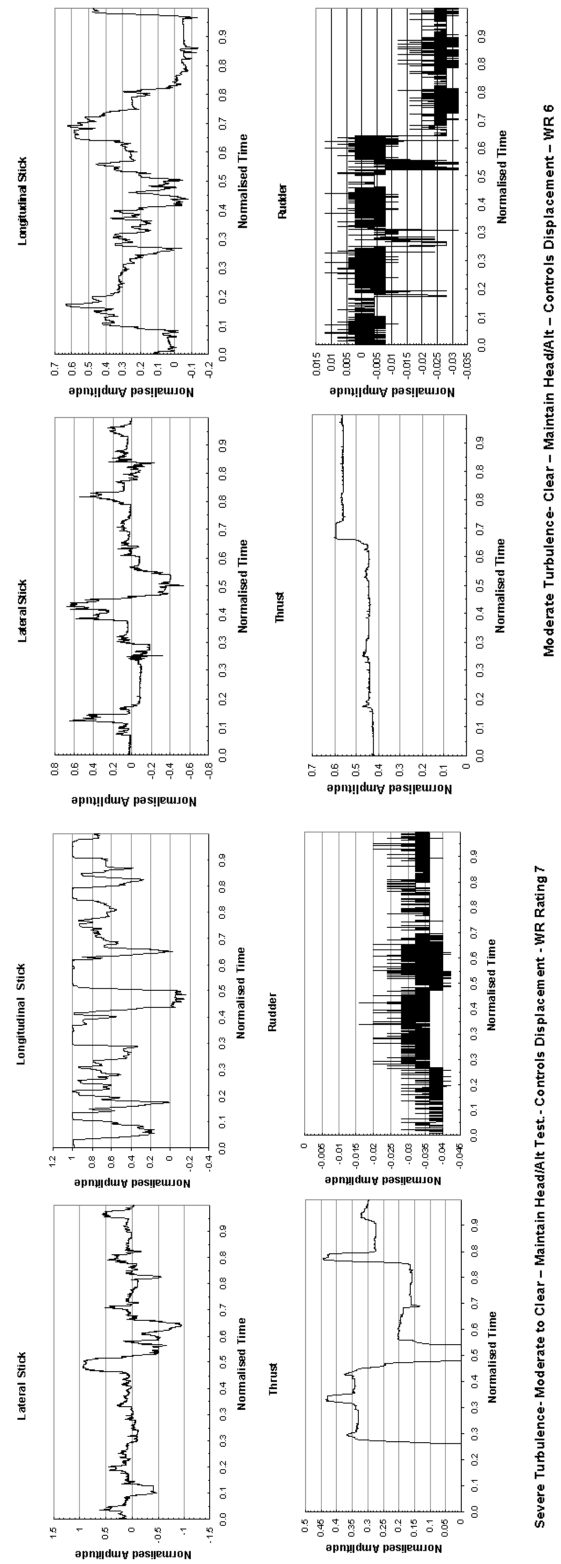


Figure A.1- Sample Data logged

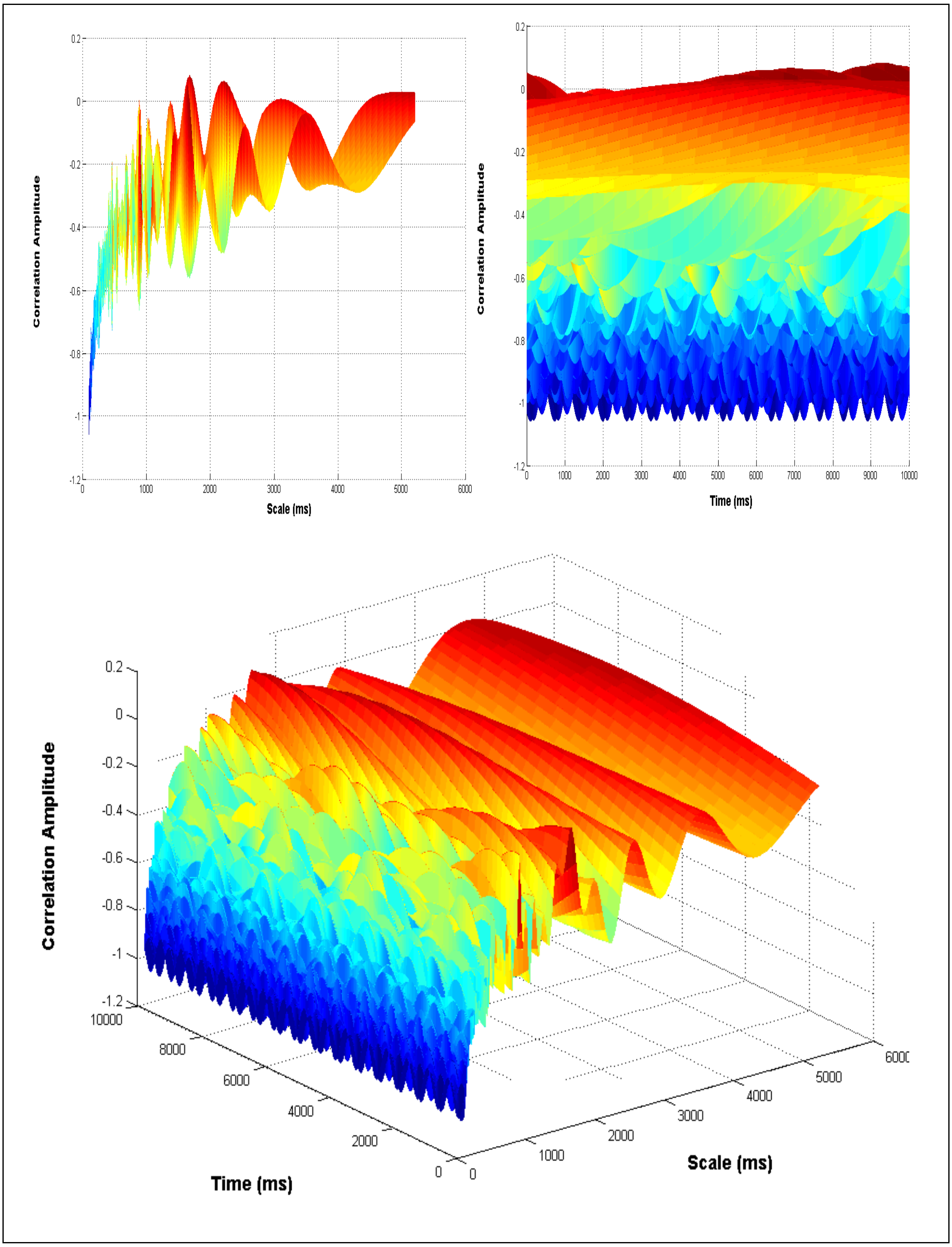


Figure A.2: Sample Surface Correlation Results for Clear Maintain Heading & Altitude Test

Table 1: Excellent convergence demonstrated after extended training (maitain head/altitude) test

	WR (none)	WR (light)	WR (mod)	WR (severe)
T+0s pattern	0.2907	0.5168	0.5899	0.7019
T+10s pattern	0.3255	0.4848	0.5844	0.6985
T+20s pattern	0.2785	0.4801	0.5799	0.7104
Average	0.2982 (want 0.3000)	0.4939 (want 0.5000)	0.5847 (want 0.6000)	0.7036 (want 0.7000)
Error	-0.0018 (<1%)	-0.0061 (<1%)	-0.0152 (<1%)	0.0036 (<1%)

Table 2: Network training performance after 10854 training loops (maitain head/altitude) test

	WR (none)	WR (light)	WR (mod)	WR (severe)
T+0s pattern	0.2103	0.5336	0.5601	0.6746
T+5s pattern	0.2357	0.4830	0.5595	0.7257
T+10s pattern	0.2844	0.4929	0.6043	0.6799
T+15s pattern	0.2877	0.5021	0.5861	0.6788
T+20s pattern	0.3783	0.4528	0.5870	0.6839
T+25s pattern	0.3445	0.5317	0.5722	0.6951
T+30s pattern	0.3087	0.5233	0.5877	0.7195
T+35s pattern	0.3039	0.5343	0.5893	0.6795
Average	0.2942 (want 0.3000)	0.5067 (want 0.5000)	0.5807 (want 0.6000)	0.6921 (want 0.7000)
Error	-0.0058 (1.9%)	0.0067 (1.3%)	-0.0193 (3.2%)	-0.0078 (1.1%)

Table 3: Unseen data workload estimation(maitain head/altitude) test

	WR (none)	WR (light)	WR (moderate)	WR (severe)
T+2s pattern	0.2265	0.4617	0.4523	0.7192
T+7s pattern	0.2574	0.4438	0.5784	0.8860
T+12s pattern	0.2649	0.4053	0.5647	0.8263
T+17s pattern	0.3155	0.3898	0.6237	0.4980
T+22s pattern	0.3905	0.5806	0.6112	0.7541
T+27s pattern	0.4024	0.4597	0.5456	0.7660
T+32s pattern	0.2644	0.5575	0.6050	0.7174
T+37s pattern	0.4028	0.5380	0.5479	0.7669
Average	0.3155 (want 0.3000)	0.4796 (want 0.5000)	0.5661 (want 0.6000)	0.7417 (want 0.7000)

Table 4: Final up-down slalom network status

	WR (none u1)	WR (none u2)	WR (light u1)	WR (light u2)
T+0s pattern	0.6110	0.7895	0.8858	0.8346
T+10s pattern	0.5927	0.8312	0.8944	0.9049
T+20s pattern	0.5852	0.8346	0.7551	0.8484
Average	0.5963 (want 0.6000)	0.8184 (want 0.8000)	0.8451 (want 0.8000)	0.8626 (want 0.9000)
Error	-0.0037 (<1%)	0.0184 (2.3%)	0.0451 (5.6%)	0.0374 (4.1%)

Table 5: Inability to discriminate between zero and light turbulence shown for wavelet analysis, maintain heading/altitude test

	WR (none)	**WR (light)**	**WR (mod)**	**WR (severe)**
T+0s pattern	0.4737	0.4529	0.7171	0.6381
T+10s pattern	0.4764	0.4901	0.6939	0.7033
T+20s pattern	0.4262	0.4494	0.4606	0.5439
Average	0.4587 (want 0.3000)	0.4642 (want 0.5000)	0.6238 (want 0.6000)	0.6284 (want 0.7000)
Error	0.1587 (53%)	-0.0358 (7.1%)	0.0238 (3.9%)	-0.0716 (10%)

Table 6: Amended WR for wavelet analysis shows convergence

	WR (none)	**WR (light)**	**WR (mod)**	**WR (severe)**
T+0s pattern	0.3300	0.3102	0.5994	0.4952
T+10s pattern	0.3296	0.3434	0.5881	0.5806
T+20s pattern	0.2884	0.3077	Unavailable	Unavailable
Average	0.3160 (want 0.3000)	0.3204 (want 0.3000)	0.5937 (want 0.6000)	0.5379 (want 0.6000)
Error	0.0160 (5.3%)	0.0204 (6.8%)	-0.0063 (1.0%)	-0.0621 (10 %)