Objective Metrics for Evaluating Flight Training Simulators

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ABSTRACT

The value of a dynamic motion platform to the flight simulator is a controversial issue within the flight training community. The motion of the flight simulator platform has been shown to affect pilot performance and behavior. Performance studies show that the operator's performance is enhanced when introducing motion which might indicate that the operator experiences a sensation closer to real flight which should reflect positively on the pilot's training. However, most transfer of training studies show no major benefit after being trained in a flight simulator with or without a motion system. Resolving these discrepancies and testing for flight simulator training effectiveness requires very time consuming and expensive testing of human performance, both in the aircraft and the simulator.

This research aims to tackle this problem by developing a control theoretic approach with novel ideas that include; developing a novel structural model of a human-in-the-loop control system, developing an algorithm which accounts for the fusion of the information from the various sensory channels based on frequency domain prominence, developing an algorithm which incorporates the effects of learning and adaptation of a human operator, investigating and implementing new vestibular, neuromuscular and somatosensory system models based on assessment in the frequency and time domain analysis.

This structural model approach permits the development of metrics for determining the training effectiveness of the simulator motion system by assessing pilot control behavior, imitating training studies and performance studies and allowing for fast designing and modification of motion systems and motion cueing algorithms objectively.

ABOUT THE AUTHORS

Ahmad Momani Received his Bachelor's and Master's degrees from Jordan University of Science and Technology and is a Ph.D. candidate of mechanical engineering at the state university of New York at Binghamton. He is currently working under the advisement of Prof. Frank Cardullo as a member of the man-machine system laboratory.

Frank Cardullo As of September 1, 2016, after 36 years at the University Professor Cardullo retired from full time service at the University and was awarded the title Emeritus Professor of Mechanical Engineering at the State University of New York at Binghamton. Prior to joining the faculty he was an engineer in the flight simulation industry for 14 years. Professor Cardullo continues to conduct research in the broad area of how humans control complex system, such as aircraft and ground vehicles, as well as telerobotics. He continues as the principal advisor to one PhD student and serves on two PhD committees. He also has been an active consultant in this area for many aerospace companies and U.S. Government agencies. He is the author of over 70 technical publications, and has been awarded a patent for the "Advanced G-Seat". Professor Cardullo has been invited to lecture at 13 different universities and research institutes in the US, Europe and Asia. He is a recipient of the AIAA De Florez Award for Flight Simulation and Training. In May 2019, he will be offering his annual week-long short course in flight simulation for the 35rd year.

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INTRODUCTION

There is a need to evaluate flight simulator elements independently of costly transfer of training studies which actually can never thoroughly completed. An example is determining the efficacy of a platform motion system in a flight simulator. The value of a dynamic motion platform to the flight simulator is a controversial issue within the flight training community. The motion of the flight simulator platform has been shown to affect pilot performance and behavior. Moreover, its ability to provide the operator with the appropriate motion cues is essential for pilot training or research. Unwanted cues can cause the operator to develop inappropriate control behavior strategies that are not useful or might be dangerous in real flight. Performance studies show that the operator's performance is enhanced when introducing motion which might indicate that the operator experiences a sensation closer to real flight which should reflect positively on the pilot's training. However, most transfer of training studies show no major benefit after being trained in a flight simulator with or without a motion system. Resolving these discrepancies and testing for flight simulator training effectiveness requires very time consuming and expensive testing of human performance, both in the aircraft and the simulator.

This paper reports on research which aims to tackle this problem by developing a control theoretic approach with novel ideas that include;

1) developing a novel structural model of a human-in-the-loop control system,
2) developing an algorithm which accounts for the fusion of the information from the various sensory channels based on frequency domain prominence,
3) developing an algorithm which incorporates the effects of learning and adaptation of a human operator,
4) investigating and implementing new vestibular, neuromuscular and somatosensory system models using frequency and time domain analyses.

This structural model approach permits the development of metrics for determining the training effectiveness of the simulator motion system, or any other simulator stimuli by measuring pilot control behavior.

BACKGROUND

The proposed control theoretic approach is in the form of a structural model of the human pilot/operator which contains blocks that mathematically represent different parts of the human perceptual and control action processes as well as the controlled vehicle. When designing man-machine systems it is assumed that the operator is having full attention to the task at hand, we can include other factors like distractions and tiresome in later research. Each block is studied and developed independently then merged in a way that simulates the overall human/vehicle operation. The output of some blocks may be analyzed, and the data used to understand the pilot behavior better. Figure 1 below shows a simplified version of the structural model where the pilot receives a reference signal based on the required task then applies the appropriate control action to the aircraft. The aircraft response to these control actions is then sensed by the pilot's different sensory systems which provide feedback that helps the pilot to control the aircraft in the desired task.

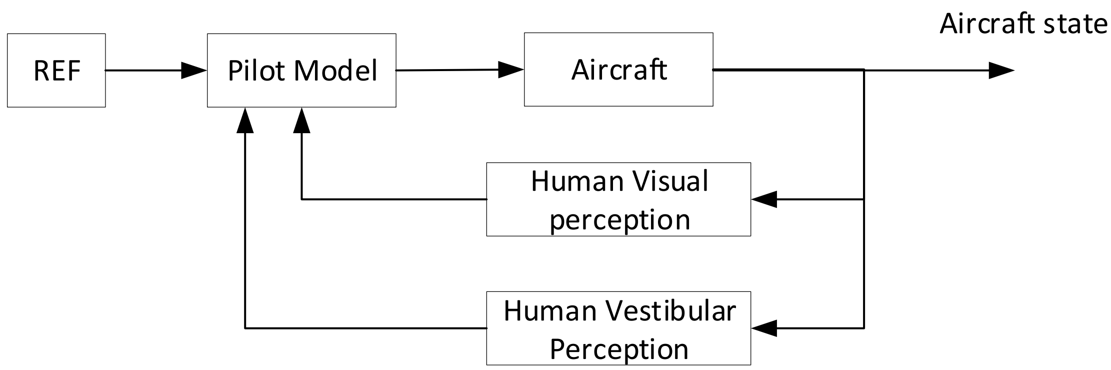


Figure 1. Simplified Model of the Man-Machine System

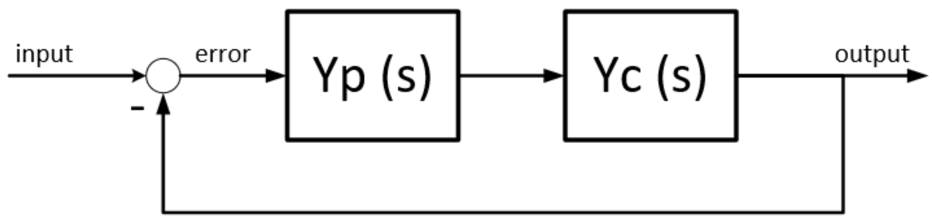


Figure 2. Crossover Model

The early concept of a mathematical model of the human pilot was introduced by McRuer (McRuer and Jex. 1967) in the form of the crossover model, the main idea behind it is the combined open loop human-vehicle input-output behavior will act as "K/jω-like" (as an integration) with a processing delay in the crossover frequency region. This model includes beside the human the controlled element dynamics (aircraft, aircraft controls, display dynamics, and manipulator dynamics) and the human is assumed to be a part of the closed-loop system where his actions evolved to a stable relationship with the controlled element due to sufficient practice. McRuer developed this model based on experiments, where the pilot performed a compensatory tracking task of random or pseudo-random input with the tracking error displayed on a CRT display in a fixed-base flight simulator (McRuer and Krendel, 1974). The parameters of the model (Crossover frequency (ωc) and effective time delay (τe)) are selected for particular situations and represent how the human pilot adjust his behavior to fulfill stable closed loop characteristics.

$$Y_p Y_c(j\omega) = \frac{\omega_c e^{-j\omega\,\tau_e}}{j\omega} \tag{1}$$

The structural isomorphic operator model is an expansion of the crossover model (see Figure 2) which aims to unite various isolated elements of the human motor coordination, physiological understanding, and neuromuscular actuation systems, and treat these subsystems as compatible ones that work together to produce an output that can be validated by the experimental data of the whole human operator.

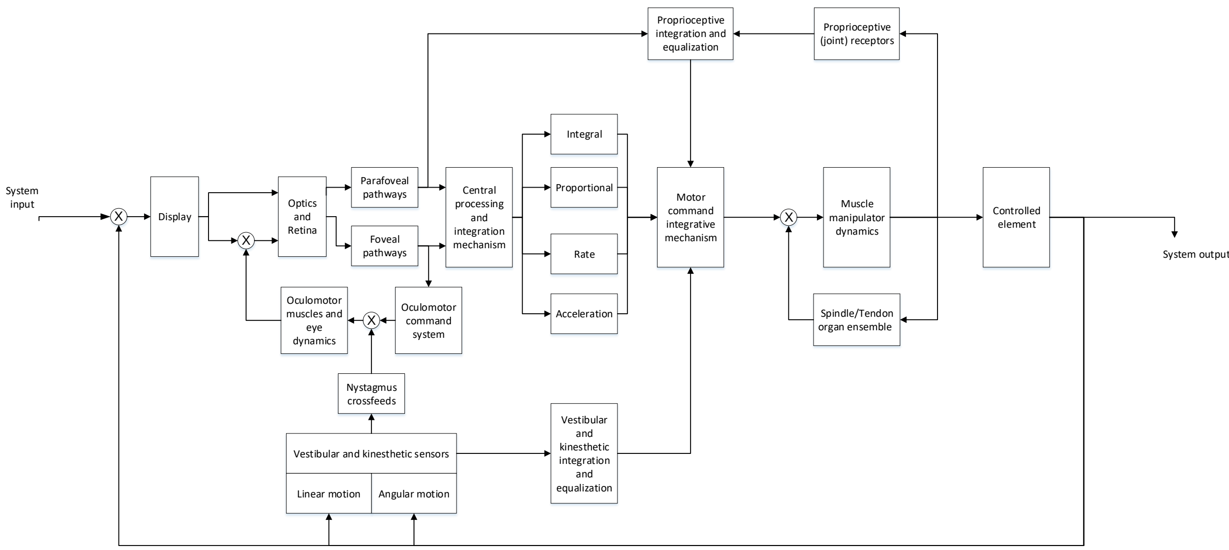


Figure 3. Structural isomorphic model of the man-machine system (McRuer and Jex. 1967)

Figure 4 shows a structural model of the human-simulator system, initially developed by Ronald Hess (Hess, 1985) which has been commonly used by previous researchers to get a general idea about the performance of the used motion system. This model contains linear models blocks that represent the human visual system, neuromuscular system, processing delay, and aircraft dynamics. Blocks that represent the flight simulator motion system in the vestibular system feedback path were added later by George and Cardullo (Cardullo, George, & Latham, 2006). The selection of these systems parameters is constrained, so the overall input-output relationship complies with the McRuer crossover model. The disadvantages of this structure that it is limited to a single axis motion and assumes a fully trained pilot, which makes it unfeasible for determining training effectiveness. Therefore, a new architecture was developed by building upon the structure of the McRuer and Hess structural models.

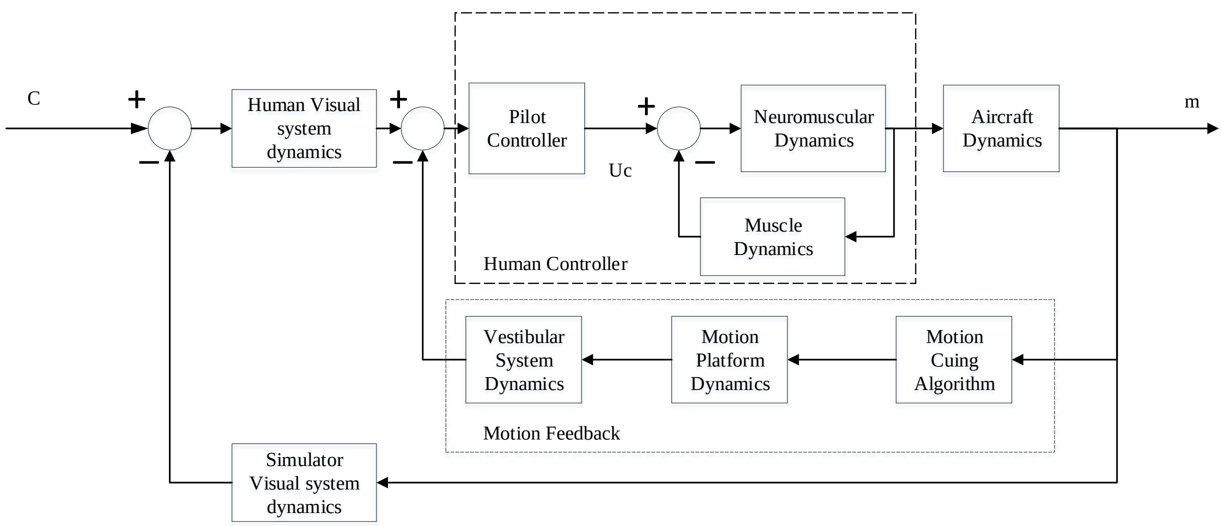


Figure 4. Simplified - Modified Hess Model (Adapted from Cardullo et al., 2006)

New Structural Model

Our architecture is a structural model of the pilot and simulator system evolved from the work of McRuer (McRuer and Jex. 1967), Hess (Hess, 1985), Cardullo and George (Cardullo, George, & Latham, 2006). It was incumbent to

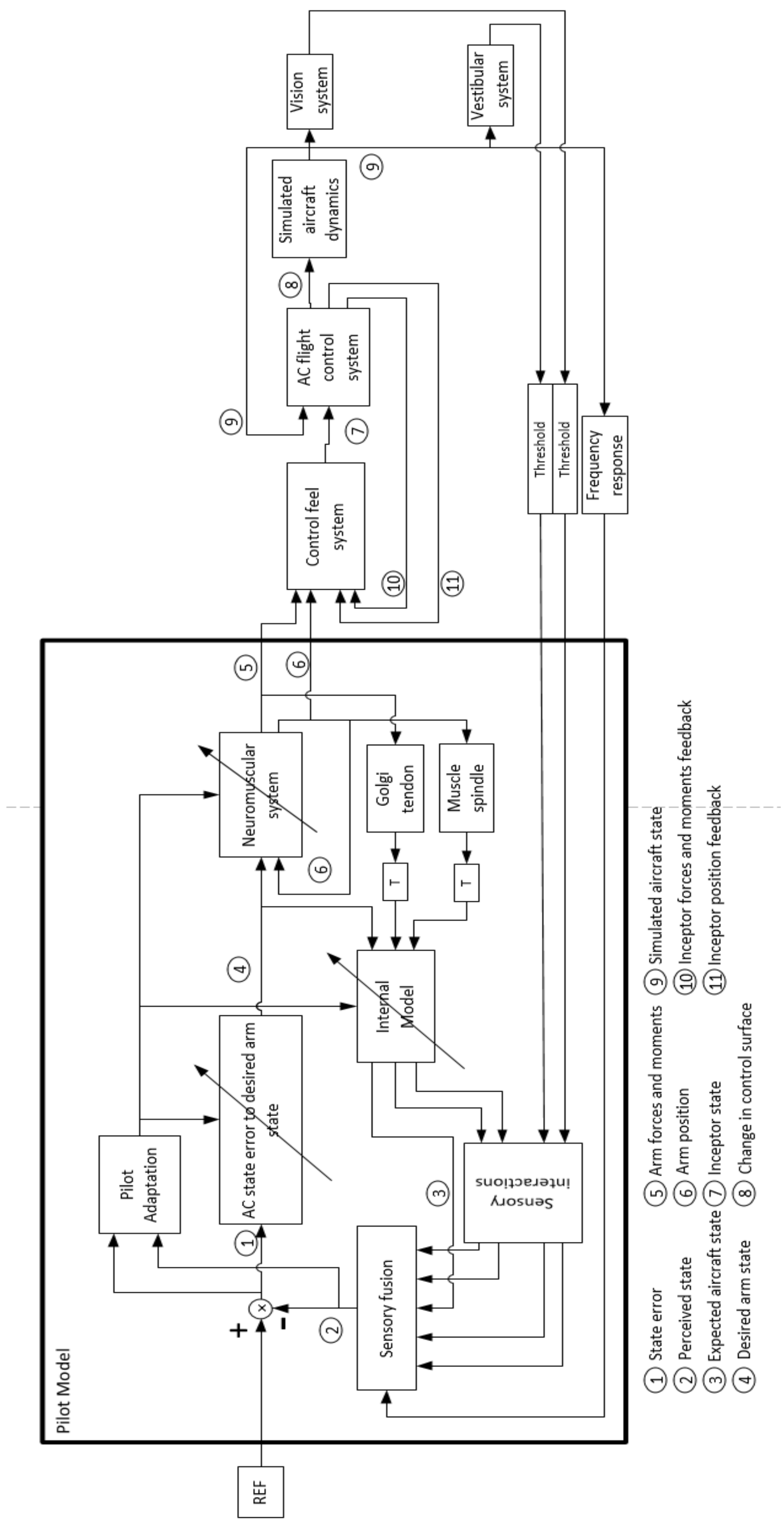


Figure 5. Detailed view of the man-machine system

incorporate the latest research on the dynamics of the vestibular and the neuromuscular systems to accomplish the goals of this research. In addition, the new architecture (Figure 5) includes the development of a sensory fusion algorithm which address the processing of information by humans. Another addition introduces an adaptation algorithm that modifies the parameters of the pilot model based on his/her behavior and represents the learning and training process uses the pilot's internal model of the aircraft dynamic response to effect control. In our structural model (figure 5), we compare the perceived state to the desired task, and the signal is used to activate the neuromuscular system. The neuromuscular system operates the feel system (e.g., aircraft inceptor and pedals) that control the aircraft, and used by the pilot's internal model of the aircraft, which is part of the pilot model and by which the pilot develops control strategy, to predict the aircraft state based on previous experience. The aircraft response stimulates the human sensory systems (vision system and vestibular system, etc.) and generates feedback to the feel system that stimulates the muscle spindles and Golgi tendons of the operator. All the sensory systems and internal model responses are aggregated together by a sensory fusion algorithm to generate the sensed state, which is processed to determine if the operator trusts his own sensed state. In addition, a learning and adaptation algorithm is employed to alter pilot behavior in response to those factors.

New Vestibular Models

The vestibular system is a complex one that combines mechanical, fluidic and neural systems that work together to provide information about the human motion to the central nervous system. Early models of the vestibular system treated it as a black box and relied on subjective data where a transfer function model was generated to represent the reported sensation by the human subject in response to a specific stimulus. Later Fernandez and Goldberg (Fernandez and Goldberg, 1971) (Goldberg and Fernandez, 1971) (Fernandez and Goldberg, 1976) recorded the afferent firing response of squirrel monkeys' semicircular canals and the otoliths, to objectively represent them by transfer functions. Recent research employs physics-based theoretical approaches to allow for further understanding of its inner working.

Semicircular canal models

For the developed structural model, the Rabbitt and Damiano semicircular canals model and Grant, Huang, and Cotton otolith model were used to represent the components of the vestibular system (Momani and Cardullo. 2018). Rabbitt and Damiano (Rabbitt and Damiano, 1992) (Damiano and Rabbitt, 1996) (Damiano, 1999) (Rabbitt, 1999) took into account the effect of semicircular canals geometry (Ifediba et al., 2007) to construct a three dimensional model that record the influence of any motion on all the canals simultaneously. We can write the governing equation that describes the system as:

$$\boldsymbol{M}\frac{d^2\overrightarrow{\boldsymbol{Q}}}{dt^2} + \boldsymbol{C}\frac{d\overrightarrow{\boldsymbol{Q}}}{dt} + \boldsymbol{K}\overrightarrow{\boldsymbol{Q}} = \overrightarrow{\boldsymbol{F}} \tag{2}$$

Where $\vec{Q} = [Q_{HC}^e \ Q_{AC}^e \ Q_{PC}^e \ Q_{HC}^c \ Q_{AC}^c \ Q_{PC}^c]'$ is the volumetric displacement vector and represent the volumetric displacement of the endolymph and cupula within the horizontal, anterior, and posterior semicircular canals, $\vec{F} = [F_{HC}^e \ F_{AC}^e \ F_{PC}^e \ F_{HC}^c \ F_{AC}^c \ F_{PC}^c]'$ is the force vector and represents the force acting on the endolymph and cupula within the horizontal, anterior, and posterior semicircular canals, M is the mass matrix, C is the damping matrix, and K is the stiffness matrix. Let X = $[\vec{Q} \quad \dot{\vec{Q}}]^T$, Y= $[\vec{Q}]^T$ then Equation (1) can be rewritten in state space form as:

$$\dot{X}_{12\times1} = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}_{12\times12} X_{12\times1} + \begin{bmatrix} 0 \\ M^{-1} \end{bmatrix}_{12\times6} \vec{F}_{6\times1} \tag{3}$$

$$Y_{6\times1} = [I_{6\times6} \quad 0_{6\times6}]_{6\times12}\, X_{12\times1}$$

Rabbitt and Damiano model has an advantage for its treatment of the semicircular canal as one system under 3D movements.

Otolith models

Grant, Huang, and Cotton (Grant, Huang, and Cotton, 1994) included in their model the effect of the otolith gel layer viscoelasticity which will yields a set of non-dimensional governing equations which provides a physically plausible response when compared to their previous research. They derived a transfer function from these equations that relate the deflection of the otolithic layer (δ_o) to the head acceleration (A). The parameters R, M, ε represent the dimensionless density, viscosity, and elasticity respectively.

$$\frac{\delta_o(s)}{A(s)} = \frac{(1-R)}{s\left[s+\sqrt{R}s+\left(\frac{\epsilon}{s}+M\right)\sqrt{\frac{Rs}{\frac{\epsilon}{s}+M}}\,coth\left(\sqrt{\frac{Rs}{\frac{\epsilon}{s}+M}}\right)\right]} \tag{4}$$

This model is preferred because it allows flexibility when dealing with the parameters of the system, permitting us to account for variations among different subjects.

These implementations include only cupula and otolith dynamics. Neural processing and thresholds needed to be added

New Neuromuscular Models

Another update of the pilot model includes a new model of the neuromuscular system. Previous models treated the neuromuscular system as a second-order model with parameters selected to make the overall model comply with McRuer crossover model. This approach is not compatible with our objectives since it assumes a fully trained pilot and its output may include a contribution from other systems (Kistemaker and Rozendaal, 2011) (Mulder et al., 2017). The parameters of the neuromuscular system and others can be altered and still comply with the crossover rule, however, the output of the neuromuscular system will change, making data collected from it unusable. Suitable neuromuscular model should depend on the physiology of the human muscles, and its parameters are independent of variations in other parts of the human model.

Magdaleno and MCRuer investigated the earliest model that discussed the neuromuscular system. They did a series of subjective and objective tests to obtain a transfer function that describes the combined dynamics of the muscle and the manipulator, and transfer functions of the spindle and joint sensors feedback. The values of the system parameters vary with task and manipulator type. (Stanco, Cardullo, Houck, Grube and Kelly, 2013)

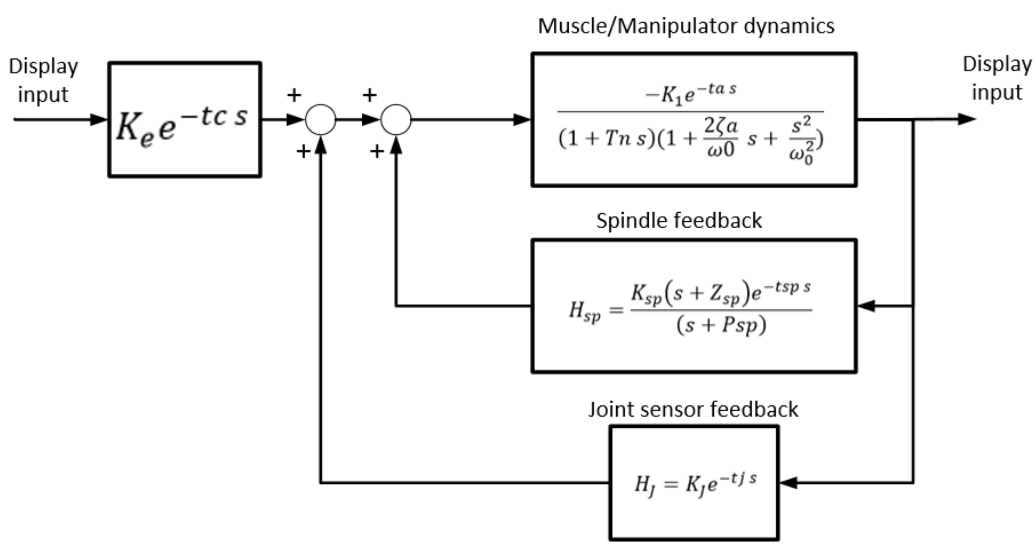


Figure 6. Neuromuscular System by Magdaleno and McRuer

Hess in his structural model, used a second-order transfer function to describe the dynamics of the neuromuscular system as a spring-damper system with a muscle spindle and Golgi tendon feedback. He chose the model parameters so that the open loop pilot-vehicle dynamics comply with the crossover model around 2 rad/sec. (Stanco, Cardullo, Houck, Grube and Kelly, 2013)

Schouten [Hosman, Cardullo, and Abbink 2010] developed a model that describes the dynamics of a one degree of freedom joint with antagonist flexor and extensor muscles assumed as one musculoskeletal system, and explain its interaction with external forces. Figure 7 shows the components of the model. (Stanco, Cardullo, Houck, Grube and Kelly, 2013)

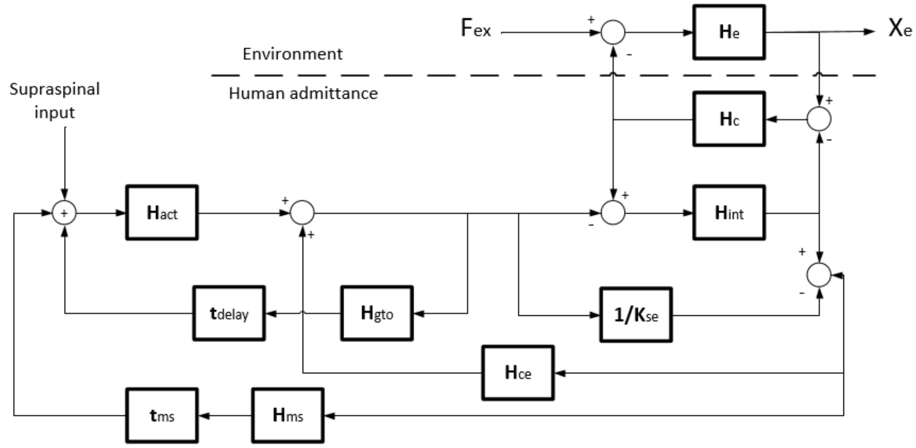


Figure 7. Schouten Neuromuscular Model

The literature presents a number of neuromuscular models based on the Hill-model approach which were considered for inclusion in the structural model (Winters and Stark, 1985) (Van Paasen, Van Der Vaart and Mulder 2004) (Van der Helm and Rozendaal 2000). The Tahara model (Tahara et al., 2005) (Tahara et al., 2009) for arm reaching movement in the horizontal plane can be used to represent the human arm dynamics controlling the aircraft motion inceptor, and thereby accounting for the nonlinear behavior of muscles combined with the dynamics of the skeletal system. It also describes the sensory-motor control problem based on the theory of stability that does not rely on inverse kinematics or optimization theory in a way that imitates the human response.

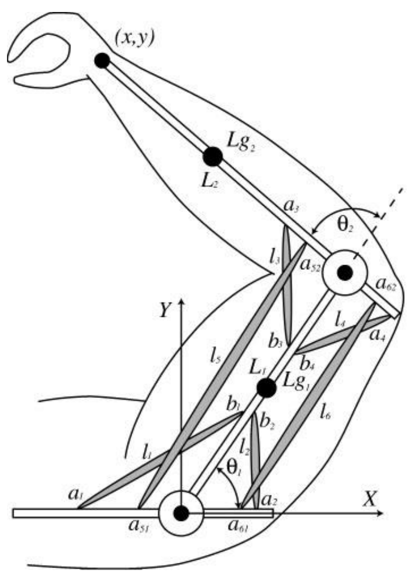


Figure 8. Detailed illustration of the model components (Tahara et al., 2005)

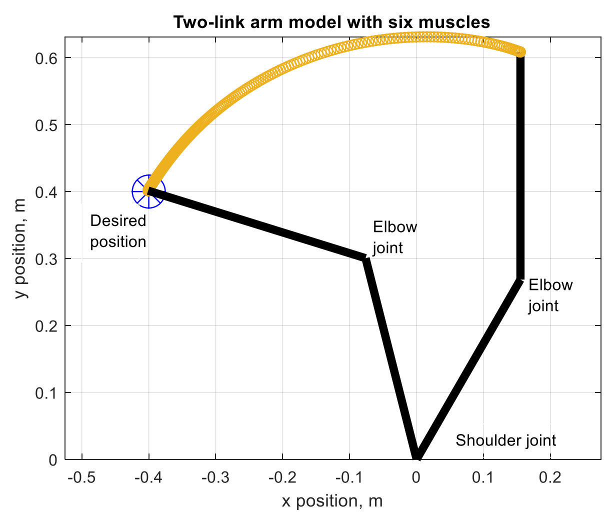


Figure 9. Matlab simulation of the model

This model consists of two parts: the dynamic equations of the skeletal system (upper arm and forearm) where the shoulder and elbow joints are assumed to work as revolute joints, and the neuromuscular system presented by the six muscles shown in figure 8 (l_1: shoulder flexor, l_2: shoulder extensor, l_3: elbow flexor, l_4: elbow extensor, l_5 double joint flexor, l_6: double-joint extensor). The forces produced by the muscles are calculated using the Hill model and is a function of the activation signal coming from the central nervous system, the forces will generate torques around the shoulder and elbow joints allowing the arm to move. The relation between muscle forces and joint torques are expressed using the principle of virtual work and the muscle space to joint space Jacobian. The torques then used as an input along with external forces acting on the hand by the inceptor to the skeletal dynamic model which is integrated to calculate the joint angles and by extension the hand position.

New Sensory Fusion Algorithm

In previous pilot models, the cues from different sensory systems are aggregated using simple summation and gains to represent the perceptual processing. However, this approach selects these gains to conform to the crossover model and does not represent the way human process his sensory information in real life. Our approach takes advantage of state of art fusion algorithms to describe the processing of the sensory cues in a way that more resembles the human. There have been a number of approaches to the solution of this problem.

The Kalman filter is an optimal estimation algorithm that utilizes a recursive method from probability theory to optimally estimate its unknown state of a dynamic system based on its mathematical model and sensory information and can be used here to estimate the overall sensed state. Previous Kalman filter models also do not incorporate the use of the pilot's internal model, or they use it in a way that represents the sensory systems instead of the aircraft. Adding the internal model gives our architecture a way to describe the learning process during training where the internal model represents the pilot understanding of the aircraft, which will be updated over time by an adaptive algorithm alongside the neuromuscular model to optimize the performance. The fusion algorithm should also take into account the contribution of different sensory systems to the overall sensed state. Different sensory systems dominate the motion perception process at different frequencies. Using the Kalman filter as a fusion method is well established in the literature, and it incorporates the use of the internal model in its structure. Varying covariance values as a function of system frequncey can alter the contribution of the sensors.

Figure 10 below shows the basic concept of a new approach using Kalman filter as a sensory fusion algorithm where the neuromuscular output along with the internal model of the aircraft is used to predict the aircraft state, and this value is corrected using the information coming from different sensory systems. While we can use Kalman filter as sensory fusion algorithm, it was designed as a state estimation method, so some modifications to its structure (sequential or parallel) are required to allow for that.

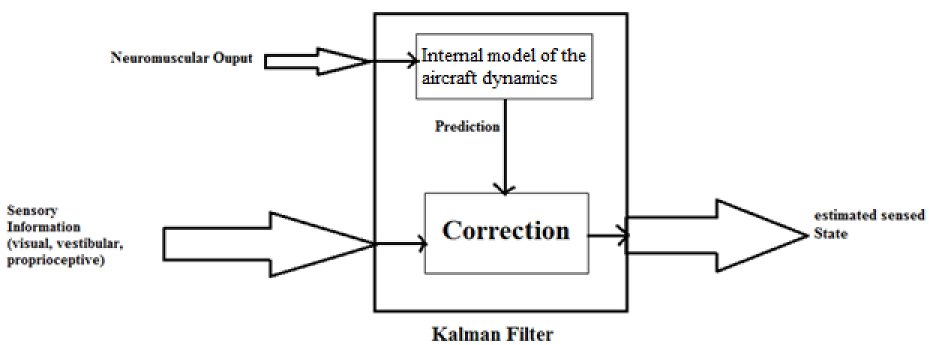


Figure 10. Kalman Filter as Sensory Fusion Algorithm in Man-Machine System

Since the band pass of the various sensory systems is different it is perhaps important to employ a fusion algorithm that accounts for this. Another approach that we can use for sensory fusion is by relying on fuzzy logic theory where we determine the contribution of each sensory system to the overall sensed state by a set of membership functions that describe each system magnitude as a function of frequencies. Figure 11 shows a notional example of such systems. At a specific frequency, we calculate the contribution of each system then the values of from each system are aggregated using the rules of the fuzzy inference system to calculate the magnitude of the relative contribution of each system.

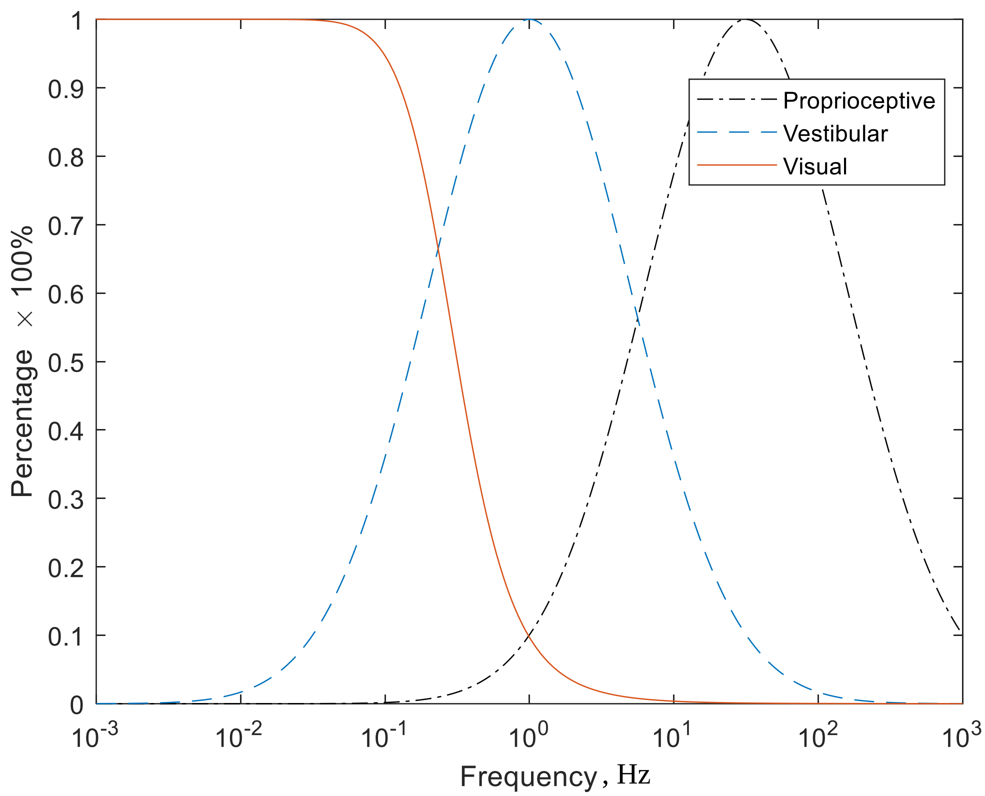


Figure 11. Notional presentation of the relative band pass of the various receptors

ANALYSIS OF THE DATA

Each element of the structural model has been executed individually (except for fusion and learning) and has produced credible results. Once we completed the additional blocks in the structural model we will execute the entire model with test cases that use simple reference inputs, and the outputs will be analyzed to determine if the operator behavior is consistent with predicted behavior (see figure 12 for context). Each path in figure 12 can be represented by our structural model, the upper path uses the model of the aircraft dynamics and the lower path uses the model of the flight simulator motion system. Upon validation of the structural model we will accomplish the evaluation of a motion cueing algorithm. We will evaluate the cueing algorithm performance in the context of our new structural model which allows us to optimize the systems that are located in the model feedback path, based on the human control behavior. Evaluating the cueing algorithm and discriminating its effect will be done at the behavioral level of the pilot (see figure 12). Pilot behaviour (performance and workload) can be objectively measured in the simulator and compared to the behavior elicited in actual flight, showing how well and how hard the operator can control a specific task. The operator control behavior will be recorded then be analyzed using various time domain and frequency domain techniques, to determine the behavioral fidelity of the pilot in the simulator. The simulation can be conducted with and without a motion system to demonstrate its effect on the pilot's performance and training effectiveness. We will execute the model with realistic flight dynamics and therefore realistic motion information provided to the operator as well as with the motion platform with typical dynamics and the various cueing algorithms thereby illustrating the effectiveness of the cueing environment.

We will evaluate the effectiveness of motion cueing in two ways based on imitating training studies and performance studies. In the first method the pilot model will initially be trained with the motion cueing algorithm and motion system in the feedback loop until it reached its training asymptote, then the resulted pilot model will be trained with the aircraft model until the training asymptote is reached again as seen in figure 13. The values of ΔP, Δt represent the difference between training asymptotes and the time needed to be fully trained after transferring from training in a flight simulator to training in aircraft. These values represent how well, and how fast the pilot can train in the flight simulator, and modifying the parameters of the motion system allow us to minimize these values.

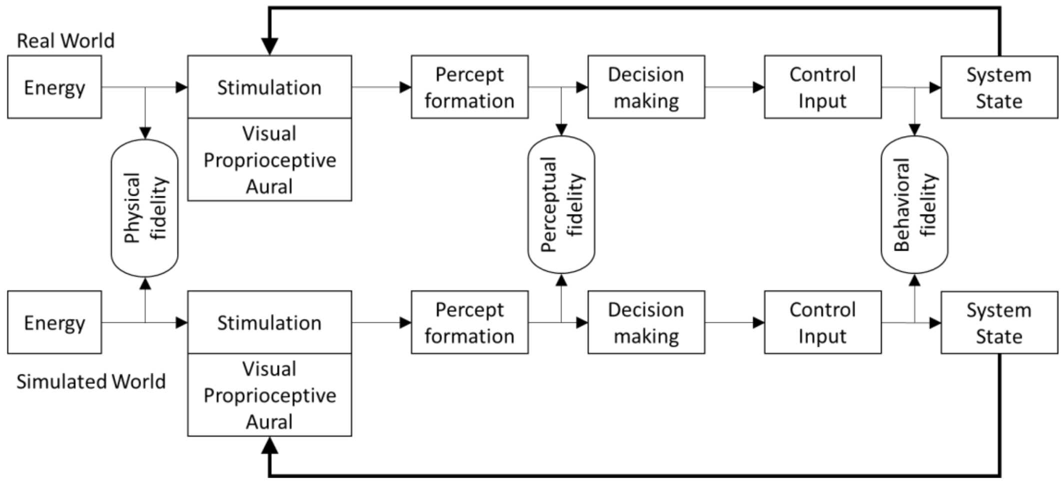
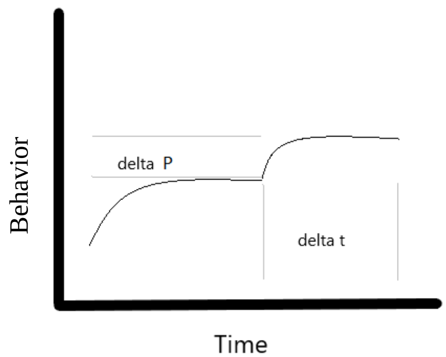


Figure 12. Virtual Environment Fidelity



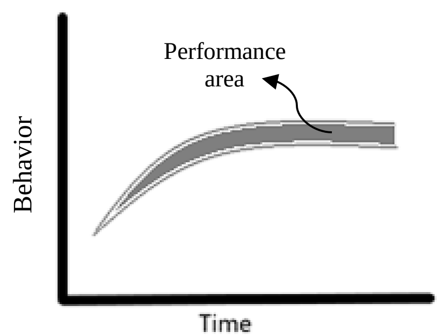


Figure 13. Training Evaluation **Figure 14. Performance Evaluation**

The second evaluation method mimics the performance studies. The initial pilot model is trained in parallel within the aircraft and flight simulator environment until they both reach their training asymptote. The area between the two curves (Figure 14) represents the performance of the motion system of the flight simulator which increases as the area value decrease.

CONCLUSION

Completing our objective metric architecture by integrating all its components and execute an evaluation of a linear and nonlinear motion cueing algorithms will allow for fast designing and modifying of motion systems objectively, which will result in better motion cueing and better-trained pilots. Furthermore it will enhance the production process of flight simulators greatly, cutting costs and save the time of various engineers and pilots who attempt to determine its fidelity in a subjective and vague process.

A major point of this proposed metric is that it can be extended to other man-machine applications besides flight simulator where the output of the human operator can be analyzed by various methods which allow mimicking the human operator and enhance the performance of different systems that are controlled by a human (e.g., vehicle design, autonomous vehicles, flight controls, surgical robots). Also other subsystem characteristics of the simulator; e.g., visual field of view, image resolution, simplified models of vehicle dynamics can be similarly evaluated.

ACKNOWLEDGMENTS

This work was partially financially supported by a Link Foundation Modeling, Simulation and PhD Training Fellowship. The authors are very grateful for their aid.

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