Time-Varying Manual Control Identification in a Stall Recovery Task under Different Simulator Motion Conditions

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This paper adds data to help develop simulator motion guidelines for stall recovery training by identifying time-varying manual control behavior in a stall recovery task under different simulator motion conditions. A study was conducted in the NASA Ames Vertical Motion Simulator, where seventeen general aviation pilots performed a stall recovery task. Pilots had to follow a flight director through four stages of the stall recovery task. A time-varying identification method was used to quantify how pilots weigh position and velocity information throughout different stages of the task, in both roll and pitch. Four motion configurations were used: no motion, generic hexapod motion, enhanced hexapod motion and full motion. Pilot performance was highest for the enhanced hexapod and full motion conditions in both roll and pitch, and the lowest for the condition with no motion. The timevarying identification method revealed that, in the roll axis, pilot position gain did not significantly change between time segments, but was the lowest for the condition with no motion. The pilot velocity gain was significantly different between motion conditions, the largest difference being found at the beginning of the stall. The enhanced hexapod motion condition had the highest pilot velocity gain. In the pitch axis, the pilot position gain was significantly different between time segments but not between motion conditions. The pitch pilot velocity gain was highest for the full motion condition and increased at the beginning of the stall, but did not change significantly for the other motion conditions. Overall, pilot control behavior under enhanced hexapod motion was more similar to that under full aircraft motion compared to standard hexapod motion. This indicates that motion cueing on hexapod simulators might be improved for stall recovery training by using the enhanced hexapod motion developed in previous experiments.

TIME-VARYING MANUAL CONTROL IDENTIFICATION IN A STALL RECOVERY TASK UNDER DIFFERENT SIMULATOR MOTION CONDITIONS

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BACKGROUND (1) – CYBERNETICS





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BACKGROUND (2) – MOTION CUEING FOR STALL RECOVERY

single-axis, time-invariant tasks

Effects of False Tilt Cues on the Training of Manual Roll Control Skills AIAA - 2015 - 0655

Effects of Heave Motion Components on Pitch Control Behavior AIAA - 2016 - 3371

Effects of Motion Cues on the Training of Multi-Axis Manual Control Skills AIAA - 2017 - 3473

Time-Varying Manual Control Identification in a Stall Recovery Task Under Different Simulator Motion Conditions AIAA - 2018 - 2936

multi-axis, time-varying tasks

Time-Varying Pilot Control Behavior Identification using MLE AIAA - 2012 - 4793

Multi-Axis Tracking Tasks with Time-Varying Motion AIAA - 2014 - 0810

Time-Varying Pilot Control Identification using Kalman Filtering AIAA - 2017 - 3666





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- 1.What are the effects of different simulator motion settings on human manual control?
- 2.How do pilots adapt their control strategies through different stages of stall recovery?
- 3.Are differences in motion the same during different stages of stall recovery?



DOUBLE-AXIS COMPENSATORY TASK





FLIGHT TASK

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No Motion(NM)

no motion cues

Generic Hexapod (GH)

typical motion by training hexapod simulators

Enhanced Hexapod (EH) eliminate translational acceleration of c.g.

Full Motion (FM) full aircraft motion

















EXPERIMENT DESIGN

- 17 general aviation pilots
- ► 32 (8x4 runs)
- Vertical Motion Simulator
- GTM model
- dependent measures
 - human manual control parameters
 - open-loop stability and phase margin
 - RMS error and control activity











- two extended Kalman filters running in parallel
- **state filter**: estimates equalization parameters
- parameter filter: estimates neuromuscular parameters
- constant time delay



DUAL EXTENDED KALMAN FILTER – EXAMPLE





RESULTS – POSITION AND VELOCITY GAINS

$Roll(\phi)$



- position gain:
 - lower for NM in t2(stall) and t3(dive)
 - no differences between time segments
- velocity gain:
 - highest for EH
 - increases towards stall (t2); lower after recovery (t4)
 - highest difference at stall (t2)



RESULTS – POSITION AND VELOCITY GAINS





- position gain:
 - no difference between motion conditions
 - decreased at(t3)
- velocity gain:
 - highest for FM
 - higher at the beginning of stall for FM



RESULTS – NEUROMUSCULAR FREQUENCY



• roll:

- no difference between motion conditions
- decreases in stall and dive
- pitch:
 - highest for FM, lowest for NM
 - decreases in stall and dive





dynamics crossover frequency

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- roll:
 - crossover frequency higher with motion
 - crossover frequency lowest in the dive(t3)
 - phase margin highest for EH
 - phase margin highest at stall (t2)

- pitch:
 - crossover frequency highest for FM
 - crossover frequency lowest at the end of the dive(t3)

t4

- phase margin lowest for EH
- highest at the end of dive(t3)



- multi-axis time-varying pilot identification in a stall recovery task
- the <u>enhanced hexapod</u> condition was the closest to the <u>full</u> <u>motion condition</u>
- pilot manual control behavior was different in roll and pitch axes
- differences in motion larger closer to stall point
- adaptive motion cueing



TIME-VARYING MANUAL CONTROL IDENTIFICATION IN A STALL RECOVERY TASK UNDER DIFFERENT SIMULATOR MOTION CONDITIONS



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EXTRA SLIDES

$$(K_p(t) + K_v(t)s)e^{-\tau_v s} \frac{\omega_n^2(t)}{s^2 + 2\zeta_n(t)\omega_n(t)s + \omega_n^2(t)}$$

$$\dot{\boldsymbol{x}}_{\boldsymbol{s}}(t) = f(\boldsymbol{x}_{\boldsymbol{s}}(t), \boldsymbol{e}(t), \boldsymbol{\theta}(t)) + \boldsymbol{w}_{\boldsymbol{s}}(t)$$
$$u(t) = g(\boldsymbol{x}_{\boldsymbol{s}}(t), \boldsymbol{\theta}(t)) + v(t)$$

$$\begin{aligned} \dot{\boldsymbol{\theta}}(t) &= \boldsymbol{w}_{\boldsymbol{p}}(t) \\ u(t) &= g(\boldsymbol{x}_{\boldsymbol{s}}(t), \boldsymbol{\theta}(t)) + v(t) \end{aligned}$$

$$oldsymbol{x_s} = egin{bmatrix} x_{s,1} & x_{s,2} & x_{s,3} & x_{s,4} & x_{s,5} & K_p & K_v \end{bmatrix}^T \ oldsymbol{ heta} = egin{bmatrix} \omega_n & \zeta_n & au_v \end{bmatrix}^T \end{cases}$$



$$Q_p = diag([0.1\omega_{n,0} \ 0.1\zeta_{n,0} \ 0.1\tau_{v,0}])$$

$$Q_s(k) = diag\left(\begin{bmatrix} 0 & 0 & 0 & 0 & q^2 \sigma_{e(k-5/\Delta t:k)}^2 & K_{p,0} & K_{v,0} \end{bmatrix}\right)$$

$$f(\boldsymbol{x}_{s}, e, \boldsymbol{\theta}) = \begin{bmatrix} x_{s,3}(12K_{p}\omega_{n}^{2}\tau_{v}^{2} + 60K_{v}\omega_{n}^{2}\tau_{v}) / \tau_{v}^{3} - \frac{x_{s,2}}{x_{s,5}} \\ e - x_{s,4}(\omega_{n}^{2}\tau_{v}^{2} + 24\zeta_{n}\omega_{n}\tau_{v} + 120) / \tau_{v}^{3} - x_{s,2}(60\tau_{v}\omega_{n}^{2} + 240\zeta_{n}\omega_{n}) / \tau_{v}^{3} - \frac{x_{s,2}}{v} \\ \cdots - x_{s,4}(\omega_{n}^{2}\tau_{v}^{3} + 24\zeta_{n}\omega_{n}\tau_{v}^{2} + 60\tau_{v}) / \tau_{v}^{3} - x_{s,5}(2\zeta_{n}\omega_{n}\tau_{v}^{3} + 12\tau_{v}^{2}) / \tau_{v}^{3} - 120x_{s,1}\omega_{n}^{2} / \tau_{v}^{3} \\ 0 \\ 0 \end{bmatrix}$$

$$g(\boldsymbol{x}_{s}, \boldsymbol{\theta}) = \begin{bmatrix} x_{s,3}(12K_{p}\omega_{n}^{2}\tau_{v}^{2} - 60K_{v}\omega_{n}^{2}\tau_{v}) / \tau_{v}^{3} - K_{v}\omega_{n}^{2}x_{s,5} + x_{s,2}(120K_{v}\omega_{n}^{2} - 60K_{p}\omega_{n}^{2}\tau_{v}) / \tau_{v}^{3} - \frac{12K_{v}\omega_{n}^{2}\tau_{v}^{2}}{v} + 120K_{p}\omega_{n}^{2}x_{s,1} / \tau_{v}^{3} \end{bmatrix}$$



KALMAN EQUATIONS

Parameter filter prediction:

$$\theta_{k}^{-} = \theta_{k-1}^{+}$$
$$P_{p,k}^{-} = \Phi_{p,k-1}P_{p,k-1}^{+}\Phi_{p,k-1}^{T} + \Gamma_{p,k-1}Q_{p}\Gamma_{p,k-1}^{T}$$

State filter prediction:

$$\boldsymbol{x}_{s,k}^{-} = \boldsymbol{x}_{s,k-1}^{+} + f(\boldsymbol{x}_{s,k-1}^{+}, e_{k-1}, \theta_{k}^{-})\Delta t$$
$$P_{s,k}^{-} = \Phi_{s,k-1}P_{s,k-1}^{+}\Phi_{s,k-1}^{T} + \Gamma_{s,k-1}Q_{s}\Gamma_{s,k-1}^{T}$$

State filter (partial) correction:

$$K_{s,k} = P_{s,k}^{-} G_{s,k}^{T} [G_{s,k} P_{s,k}^{-} G_{s,k}^{T} + R]^{-1}$$

$$P_{s,k}^{+} = (I - K_{s,k} G_{s,k}) P_{s,k}^{-} (I - K_{s,k} G_{s,k})^{T} + K_{s,k} R K_{s,k}^{T}$$

Parameter filter correction:

$$\begin{split} K_{p,k} &= P_{p,k}^{-} (G_{p,k}^{tot})^{T} [G_{p,k}^{tot} P_{p,k}^{-} (G_{p,k}^{tot})^{T} + R]^{-1} \\ \boldsymbol{\theta}_{k}^{+} &= \boldsymbol{\theta}_{k}^{-} + K_{p,k} [u_{k} - g(\boldsymbol{x}_{s,k}^{-}, e_{k}, \boldsymbol{\theta}_{k}^{-})] \\ P_{p,k}^{+} &= (I - K_{p,k} G_{p,k}^{tot}) P_{p,k}^{-} (I - K_{p,k} G_{p,k}^{tot})^{T} + K_{p,k} R K_{p,k}^{T} \end{split}$$



RMS E, U







FLIGHT CHARACTERISTICS



