52nd IEEE Conference on Decision and Control
Florence, Italy
December 10-13, 2013

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LABORATORY FOR INTELLIGENT SYSTEMS AND CONTROLS

Modeling Human Pilots with Artificial Neural Networks

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Introduction

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Motivation

- Applications of Human Pilot Models or Human Driver Models (HDM)

  A. Automotive Industry - Simulate vehicle performance prior to manufacturing

  B. Aircraft Industry

  C. Haptic Assistance Systems

  D. Autonomous Vehicle Control

- <u>Traditional</u> approach uses model predictive control (MPC), also known as receding horizon control (RHC)
- <u>New</u> approach uses artificial neural networks (ANN)
- LISC Research Emphasis: Human Driver Models for ground vehicle control using ANNs.

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Related Work

[1] P. Falcone, M. Tufo, F. Borrelli, J. Asgari, and H. Tseng, “A linear time varying model predictive control approach to the integrated vehicle dynamics control problem in autonomous systems,” in Decision and Control, 2007 46th IEEE Conference on, dec. 2007, pp. 2980 –2985.

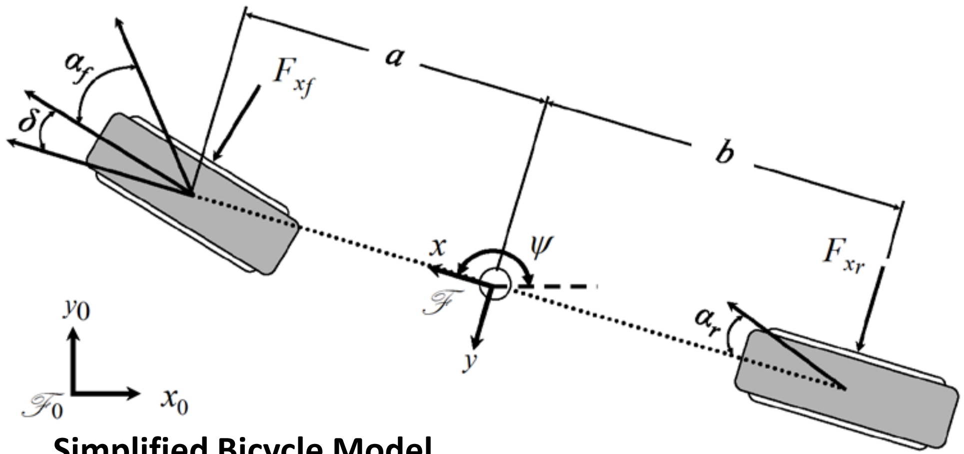
[2] V. Akpan and G. Hassapis, “Adaptive predictive control using recurrent neural network identification,” in Control and Automation, 2009. MED ’09. 17th Mediterranean Conference on, june 2009, pp. 61 –66.

[3] R. Hess and A. Modjtahedzadeh, “A control theoretic model of driver steering behavior,” Control Systems Magazine, IEEE, vol. 10, no. 5, pp. 3–8, Aug 1990.

Mathematical Models

Model of Lateral Vehicle Dynamics

- The simplified bicycle model is commonly used to describe vehicle dynamics.
- This model is used as the plant model in the RHC controller.
- The lateral and longitudinal dynamics of the model are described separately but are coupled.



Simplified Bicycle Model

Newton's II Law in the y-direction.

$$m(\ddot{y} + \dot{\psi}\dot{x}) = F_{yr} + F_{yf}$$

$$I_z\ddot{\psi} = aF_{yf} - bF_{yr}$$

Lateral Forces

$$F_{y_f} = K_f\alpha_f$$

$$F_{y_r} = K_r\alpha_r$$

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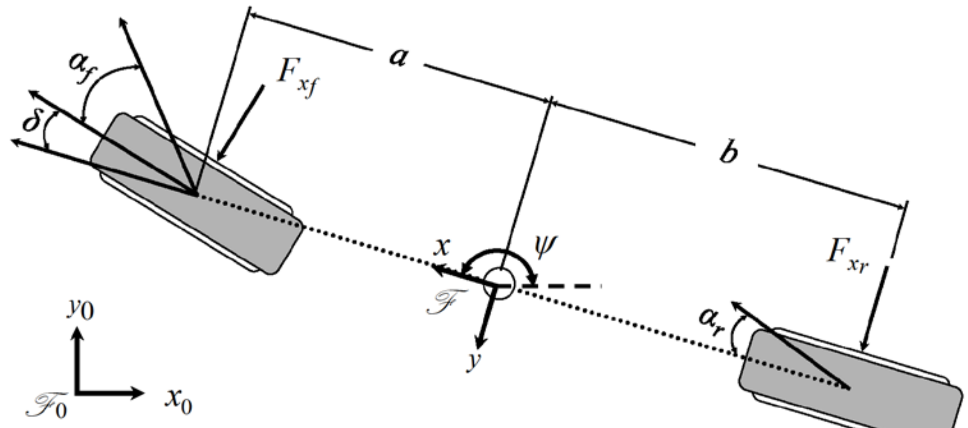
Model of Lateral Vehicle Dynamics

- The state-space representation of the model is that of a standard time invariant linear system for for the lateral dynamics.

- A similar model of higher dimension is used in the high fidelity Ferrari GT simulator.



Simplified Bicycle Model

Tire Relaxation Rates

$$\frac{l_f}{\dot{x}}\dot{\alpha}_f + \alpha_f = \delta - \frac{a\dot{\psi} + \dot{y}}{\dot{x}}$$

$$\frac{l_r}{\dot{x}}\dot{\alpha}_r + \alpha_r = \frac{b\dot{\psi} + \dot{y}}{\dot{x}}$$

State Space Lateral Vehicle Model

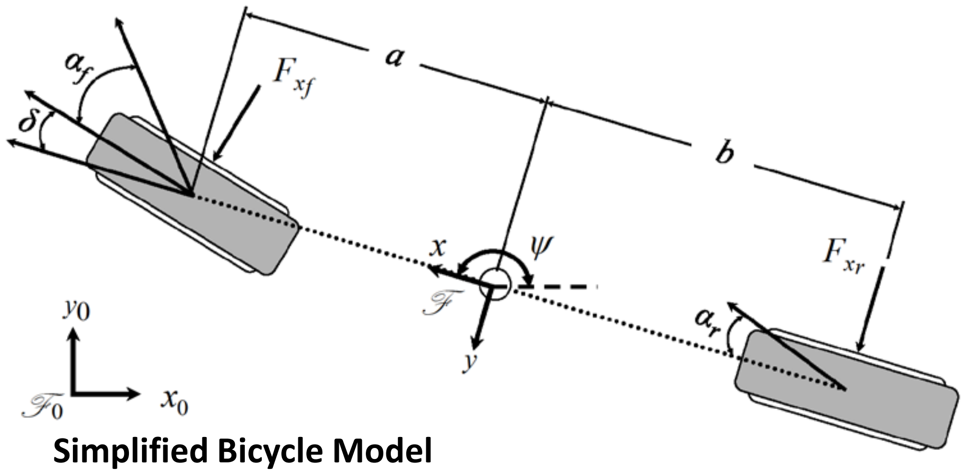
$$\dot{\mathbf{x}}_y = \mathbf{A}\mathbf{x}_y + \mathbf{B}\mathbf{u}_y$$

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -\dot{x} & K_f/m & K_r/m \\ 0 & 0 & aK_f/I_z & -bK_r/I_z & \\ 0 & -1/l_f & -a/l_f & -\dot{x}/l_f & 0 \\ 0 & -1/l_r & b/l_r & 0 & -\dot{x}/l_r \end{bmatrix}$$

$$\mathbf{B} = [0 \quad 0 \quad 0 \quad \dot{x}/l_f \quad 0]^T$$

Model of Longitudinal Vehicle Dynamics

- Notes and eqns here.

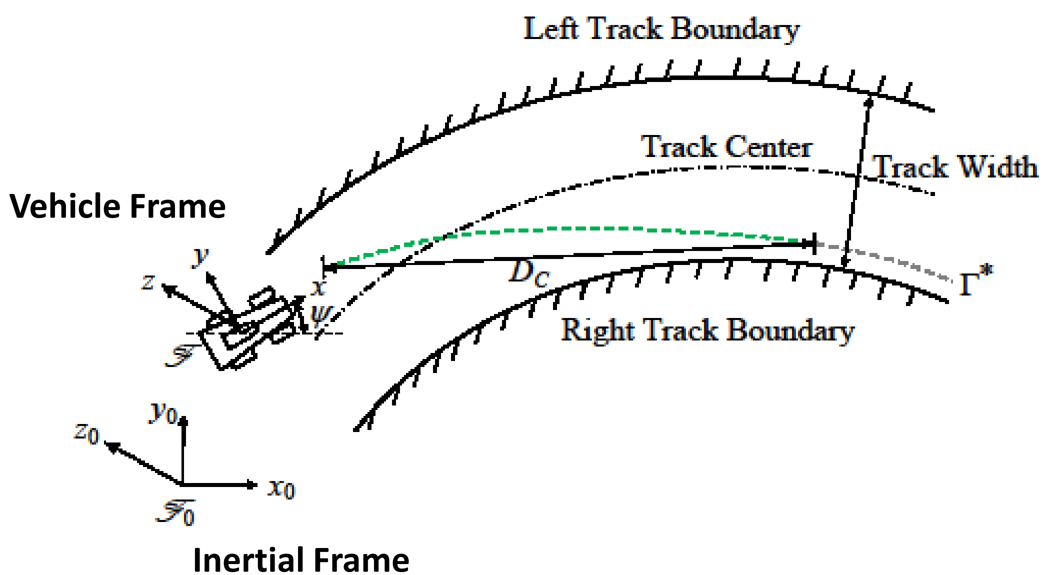


Simplified Bicycle Model

Problem Formulation

Problem Formulation

- This is a trajectory following control problem
- The pilot model accepts as inputs the same information a human driver would use to drive a ground vehicle (ex. Vehicle state: speed, RPM, etc..)
- The pilot model determines as output the optimal control for the vehicle to follow the desired trajectory (ex. track and speed profile).



Variables

p – Simulation Parameters, **p** = $[P_t \; D_{min}]$

P_t is the preview time in seconds

D_{min} is the minimum preview distance, $D = V * P_t$

$\boldsymbol{V}^*$ - Target Speed Profile defines the goal speed of the vehicle at points along the track.

$\boldsymbol{\Gamma}^*$ – Target Diver Line, $\boldsymbol{\Gamma} = [X_{\boldsymbol{t}}^* \; Y_{\boldsymbol{t}}^* \; Z_{\boldsymbol{t}}^*]$

$[X_{\boldsymbol{t}}^* \; Y_{\boldsymbol{t}}^* \; Z_{\boldsymbol{t}}^*]$ is the goal coordinates of the c.o.g. of the vehicle w.r.t. the inertial frame of reference

x – observable state, **x** = $[\, \dot{x} \; \ddot{x} \; RPM]$

$\dot{x}$ is longitudinal speed

$\ddot{x}$ is longitudinal acceleration

RPM is the engine revolutions per minute

Variables

u – control input, **u** = [η P_c G λ δ]

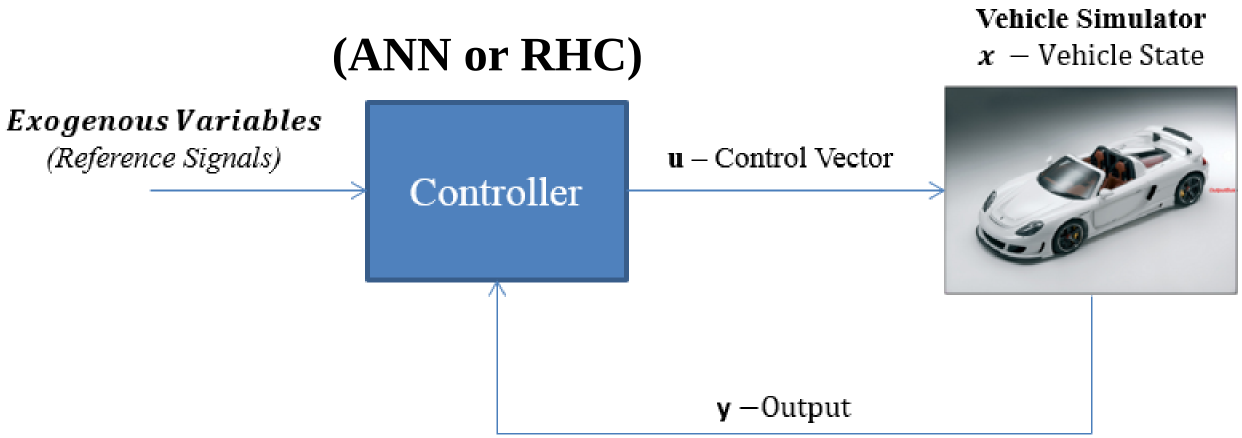
η is percentage of brake, $0 \le \eta \le 100$

P_c is percentage of clutch, $0 \le P_c \le 100$

G is the discrete gear value, $G \in \{1,2,3,4,5,6\}$

λ is the percentage of accelerator, $0 \le \lambda \le 100$

δ is the steering angle, $\delta_{min} \le \delta \le \delta_{max}$



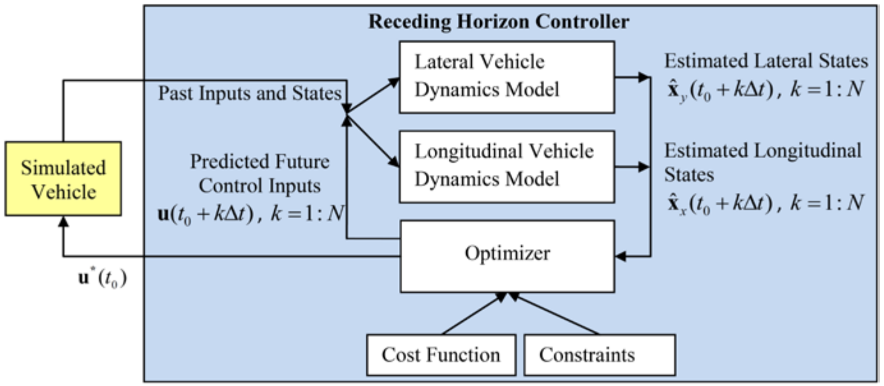
System Diagram with Simulator

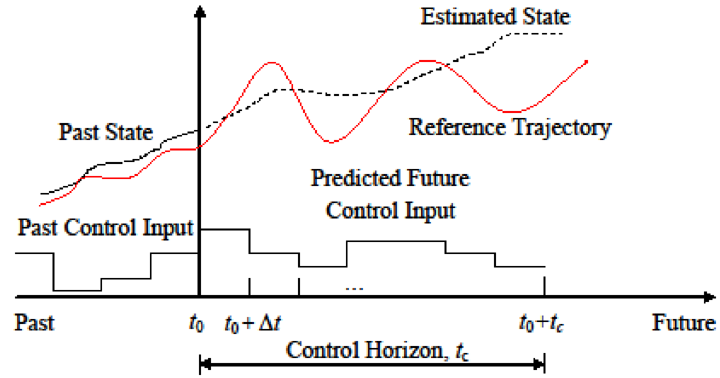
Methodology

Receding Horizon Controller Based Human Driver Model (RHC-HDM)

RHC Design

- The bicycle model is used for the lateral and longitudinal dynamical models in the RHC.
- The cost function is simply the L2 norm between the velocity trajectory, positional trajectory, and yaw angle trajectory.





Cost Functions

$$J_x(\mathbf{u}_x, \mathbf{x}_x(t_0), t_c) = \|[\hat{\dot{x}}(t_0+\Delta t) \quad \dots \quad \hat{\dot{x}}(t_0+N\Delta t)] - \mathbf{V}^*\|_2$$

$$J_y(\mathbf{u}_y, \mathbf{x}_y(t_0), t_c) = \|[\hat{\psi}(t_0+\Delta t) \quad \dots \quad \hat{\psi}(t_0+N\Delta t)] - [\psi^*(t_0+\Delta t) \quad \dots \quad \psi^*(t_0+N\Delta t)]\|_2$$

Methodology

Artificial Neural Network Based Human Driver Model (ANN-HDM)

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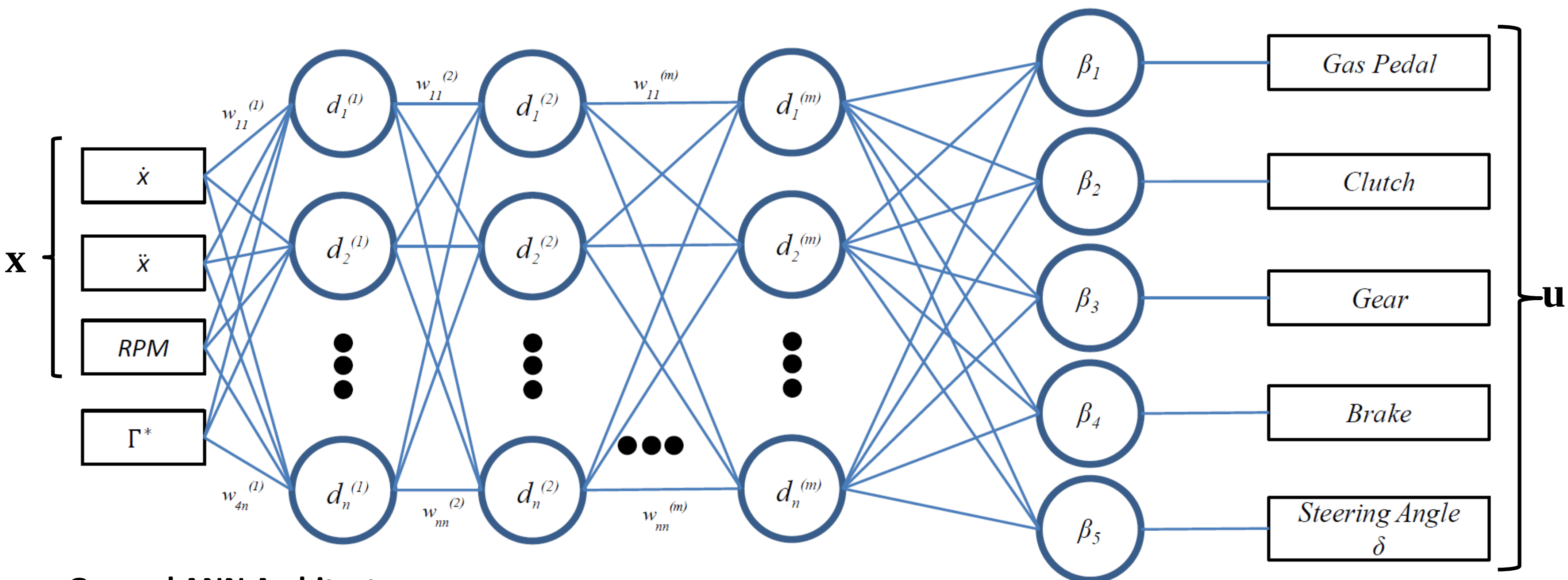
ANN Structure

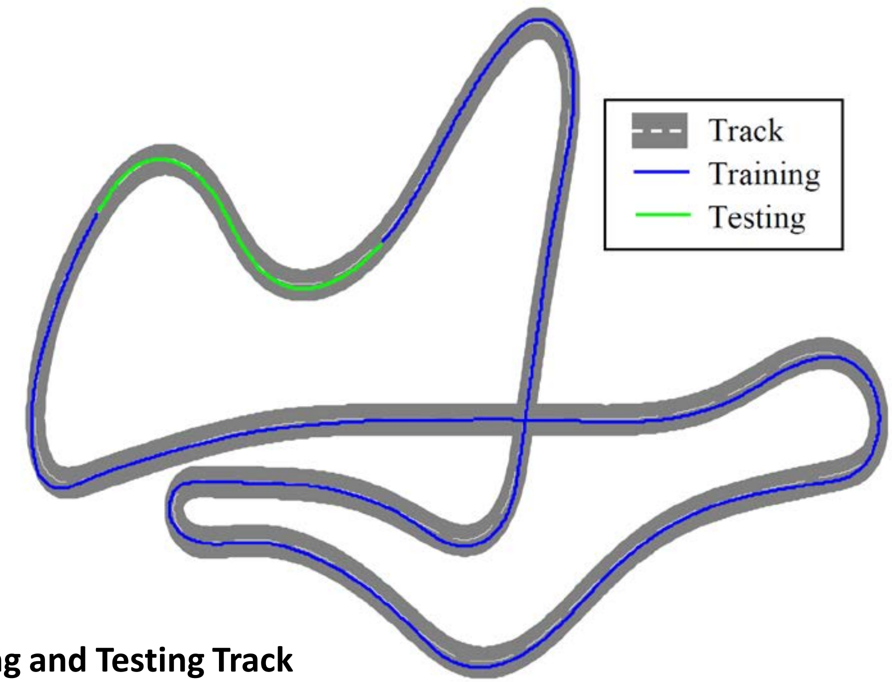
- The ANN is a standard feed-forward network with multiple inputs and outputs.
- Actually, one network for each output is trained separately and the networks are run in parallel to create the controller similar to the one shown below.
- Each circle represent a summation and transfer function with associated inputs weights *w* and bias *d*. β's are linear functions evaluated on the outputs from the last hidden layer.
- For the purpose of our ANN, the driver line is our optimal trajectory



General ANN Architecture

ANN Training

- Data from a professional human driver on a high-fidelity Ferrari GT Vehicle Simulator is used for training of the neural network.
- We have ~7500 data points in the data set with 75% used for training.
- The data points are separated in time by 0.01 seconds while the pilot drives the vehicle around the track – high resolution.
- Trained using Levenberg-Marquardt (LM) backpropogation algorithm, standard with the Matlab Neural Network Function Fitting Toolbox



Training and Testing Track

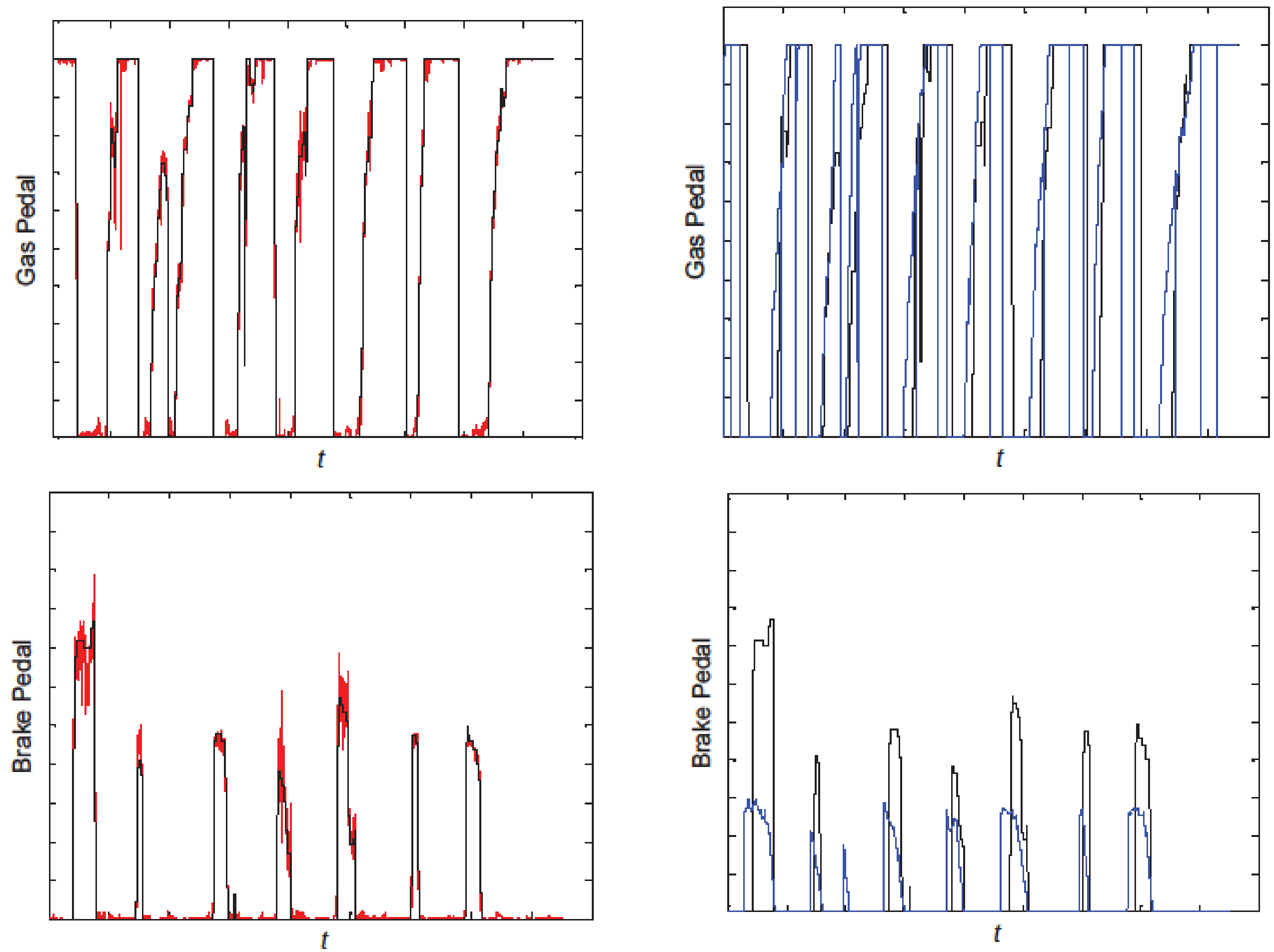
Simulations and Results

Results: Gas and Brake Pedals

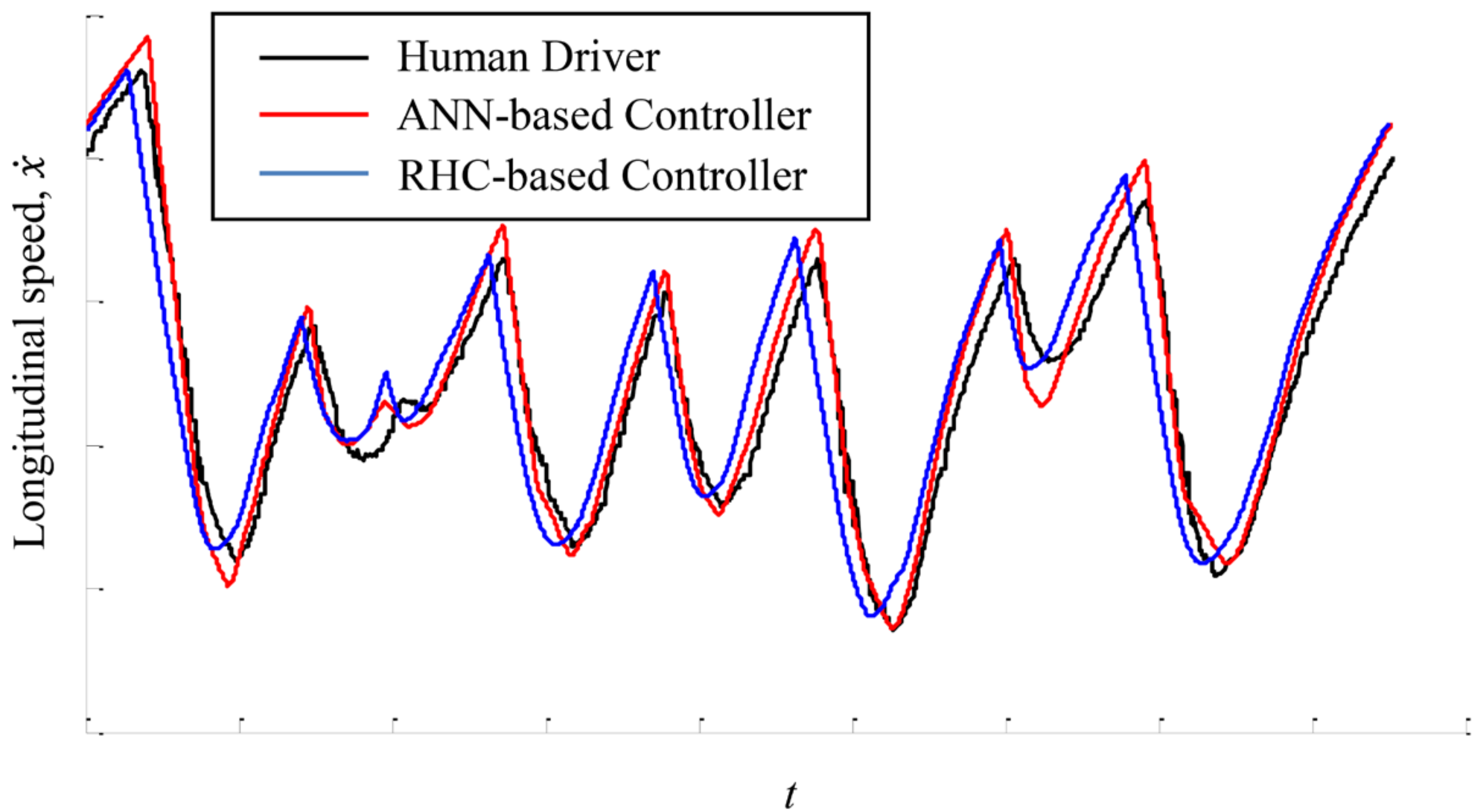
ANN Based Controller

RHC Based Controller

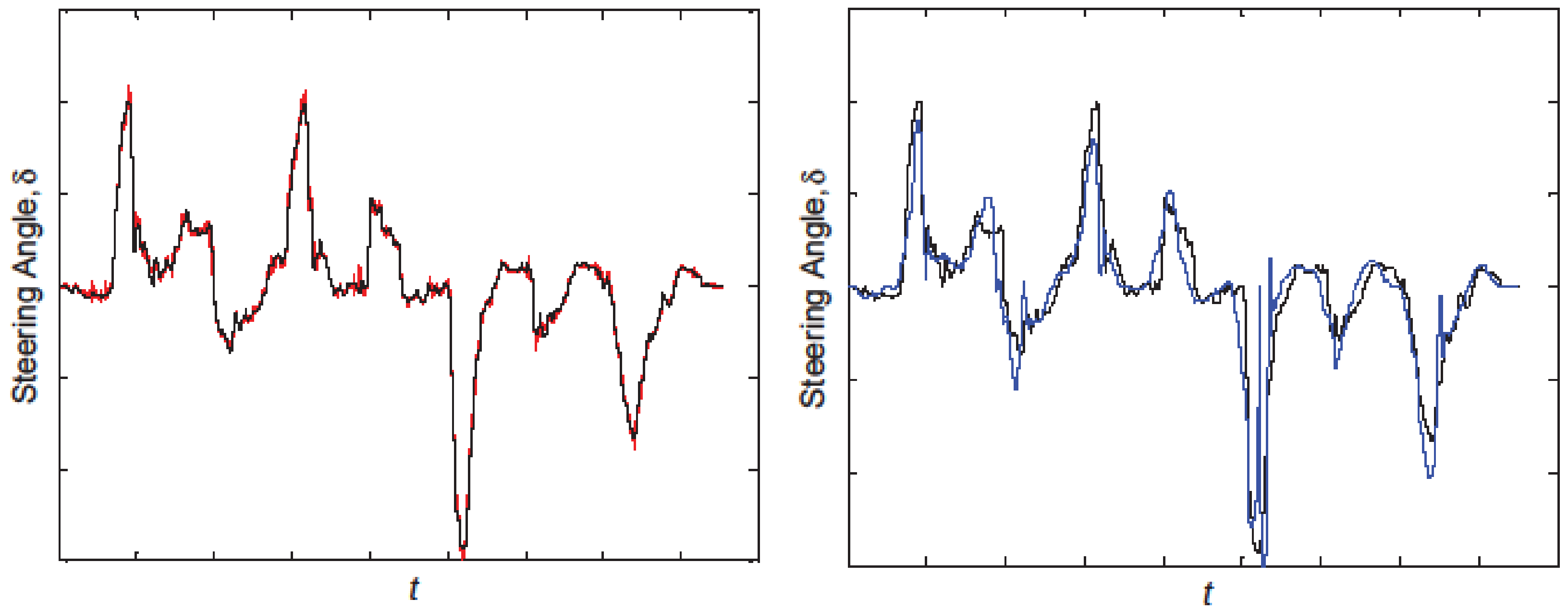
Human Driver



Results: Velocity Profile Tracking



Results: Steering Angle

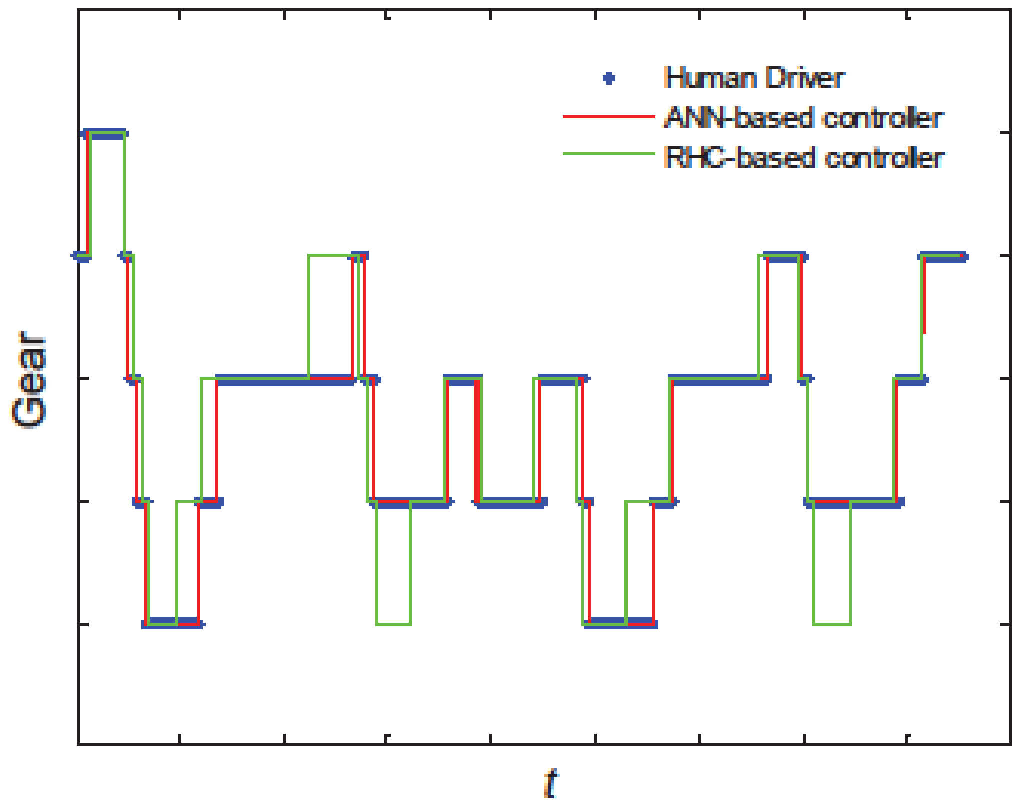


ANN Based Controller

RHC Based Controller

Human Driver

Results: Gear



Conclusions and Future Work

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Conclusions

Summary

- An artificial neural network is used to model a human pilot for driving a vehicle.
- The ANN is a feed-forward network trained with real data collected from a professional human driver.
- The ANN generated control inputs for the vehicle that matched very well with the response of the human pilot.
- The ANN input/output mapping more closely matched that of the professional human driver than did the RHC output.

Conclusions

- There appears to be a mapping between vehicle state and human driver control inputs for a vehicle.
- The ANN is capable of finding such a mapping.
- An ANN based HDM will be more "human like" than other, traditional controllers such as RHC.

Current and Future Work

- The structure of the ANN including choices for inputs and training set size can be changed to improve performance.

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References

[1] P. Falcone, M. Tufo, F. Borrelli, J. Asgari, and H. Tseng, “A linear time varying model predictive control approach to the integrated vehicle dynamics control problem in autonomous systems,” in Decision and Control, 2007 46th IEEE Conference on, dec. 2007, pp. 2980 –2985.

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