Precision Control of Autonomous Vehicle under Slip Using Artificial Neural Network

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***Abstract*: This work presents "precision control of autonomous vehicle under slip using artificial neural network". The work was achieved using FCN LSTM slip dataset, dynamic model of the vehicle, nonlinear slip model, feature extraction model, artificial neural network and simulink. The neural network was trained using back propagation algorithm. The training performance of the neural network was analyzed using a regression analyzer to evaluate the training validation performance with slip estimation accuracy of 99%.**

***Keywords*: training, testing, artificial neural network, feature extraction, slip**

I. INTRODUCTION

According to [1], over 900 million individuals travel by car all over the world every day. However, despite the importance of this great locomotive invention of mankind, it equally means that over 900 million people stand the risk of accident daily. The evidence is there for all to see in the news, social media, along the highways among others. According to the road traffic accident system (RTA) over 1.2 million deaths and 50 million people are injured every year due to road crash [2] and this has remained a very big problem till date. The main cause of this problem includes the unreliable psychological nature of most driver body condition which when subjected to stress or fatigue affects level of concentration on high ways. Other reasons for accident includes during driving, lack of detailed driving experience, bad roads, weather conditions, faults on the vehicles like bad tyres bursting while on high speed and lots more.

For over fifty years various techniques discussed in [3] have been proposed to combat this road sadness. However despite the success recorded, there is still need for complete vehicle cruise automation. [4] Identified autonomous vehicles with high level of intelligence to sense disturbance, over speeding and other nonlinear input and take necessary control precaution is the solution.

To achieve this, several works have been proposed, using different intelligent techniques, but however, despite the success achieved so far, certain constraints affect the complete system reliability, operational effectiveness and automation of the technology [5]. Among these constraints is slip force. It is the angle between the tyre and road surface, with the capacity to change the dynamics of vehicle, upsetting stability and cruise control linearity. This slip force is a major challenge affecting the stability of autonomous vehicles during speed and is difficult to control in real time. This paper therefore presents an artificial intelligence system which be trained with slip dataset to control this problem and stabilize the vehicle once nonlinearity is detected as a result of slip. This will be achieved in the research developing a model of the autonomous vehicle during translation, modeling the slip which affect the stability of the vehicle and training a neural network algorithm for the approximation and control of the vehicle during under the effect of slip.

II. METHODOLOGY

The system was developed using slip data collected from [5] to train a neural network controller which extracts slip effects nonlinear vehicle behaviour, then train it to classify nonlinearity and then stability then control the vehicle or stability. The block diagram was presented in figure 3.1;

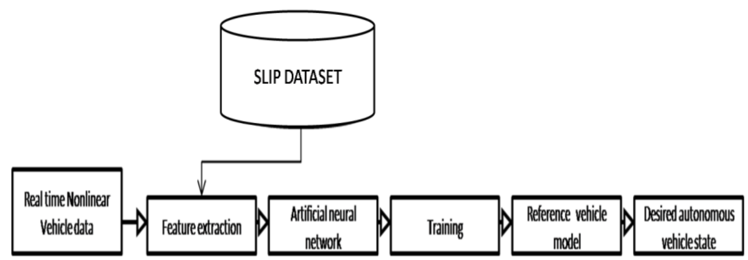

Figure 1: system block diagram

III. SYSTEM DESIGN

The system design will be developed using the dynamic vehicle state space model under motion, the slip model, feature extraction model, nonlinear grey box model, nonlinear auto regressive model, training model.

Model of the vehicle dynamics

This section describes the mathematical model of the autonomous vehicle dynamics, considering the longitudinal velocity, lateral velocity, the yaw rate about the point of gravity and tire slip angles. This model will be defined considering Newton law of motion connecting the variables already mentioned using differential equations as shown in equation 1;

$$\frac{d}{dt} V_x(t) = V_y(t) * r(t) + \frac{1}{m} * (F_x F_l(t) + F_x F_r(t)) * \cos(\text{delta}(t)) * \sin(\text{delta}(t)) + F_X R_l(t) + F_x R_r(t) - CA * V_x(t)^2 \qquad \text{Equation 1}$$

Where the longitudinal vehicle velocity is Vx(t); Vy(t) is longitudinal acceleration, r(t) is yaw rate, $F_x F_l$ is the left front tyre, $F_x F_r$ is the right front tyre, $F_X R_l$ is the right rear tyre, $F_x F_r$ is the right front tyre, delta is the steering angle, and CA is the center of gravity. Considering the vehicle state space model under acceleration presented the equation 2;

$$\frac{d}{dt} V_y(t) = V_x(t) * r(t) + \frac{1}{m} * (F_x F_l(t) + F_x F_r(t)) * cos(delta(t)) * sin(delta(t)) + F_X R_l(t) + F_x R_r(t) \qquad Equation\ 2$$

Where V_y is the lateral velocity and V_x lateral acceleration. Considering the model in equation 1 and 2with inertia with respect to the point of gravity presented the vehicle model in equation 3;

$$\frac{d}{dt} r(t) + \frac{1}{J} (a) * (F_x F_l(t) + F_x F_r(t)) * \sin(\text{delta}(t)) * \cos(\text{delta}(t)) + F_y R_l(t) + F_y R_r(t) \qquad \text{Equation 3}$$

Where J is the moment of inertia, a and b are the distance from the center of gravity to the front and rear axles respectively. Applying force and slip on the model in equation 3 presents the vehicle behavior in equation 4 and 5;

$$F_{x,i(t)} = C_x * si_{(t)} \qquad \text{Equation 4}$$

$$F_{y,i(t)} = C_y * alphai_{(t)} \qquad \text{Equation 5}$$

Where Cx and Cy are the longitudinal and lateral tire stiffness respectively, i is the (FL, FR, RL,RR) wheels when the stiffness is the same for the four wheels (i) then the longitudinal slip is presented as si(t) and the tire slip angle is alpha i(t).

Vehicle translational Model

To develop the vehicle model under motion, force id applied on equation (1 to 3) to calculate the translational motion of the body fixed coordinates frame. This force applied is the resultant relationship between the longitudinal force Fx, lateral force Fy and yaw rate Fz to estimate the rotational force F_B acting on the tyres. Relating this vehicle body whose origin is fixed coordinated in the center of gravity. The mass of the vehicle body m is assumed constant, where the applied force $[Fx, Fy, Fz]^T$ in the body fixed frame and velocity V is defined as;

$$F_B = \begin{bmatrix} Fx \\ Fy \\ Fz \end{bmatrix} = m\,(V + \omega \times V) \qquad \text{equation 6}$$

Where $M_b = \begin{bmatrix} L \\ M \\ N \end{bmatrix} = I\omega + \omega \times (I\omega)$; $I = \begin{bmatrix} Ixx & -Ixy & -Ixz \\ -Iyx & Iyy & -Iyz \\ -Izx & -Izy & Izz \end{bmatrix}$

Where M_b is the mass between the front and the rear tyres, I is the vehicle moment body of inertia along x,y and z axes.

Now to derive the relation between the fixed angular velocity vector of the body $[p\ q\ r]^T$, and the rate of Euler angle variation $[\varphi\ \Theta\ \psi]^T$, this is designed furnishing the fixed body frame with the Euler rate as presented in the structure below;

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} \varphi \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\varphi & sin\varphi \\ 0 & -sin\varphi & cos\varphi \end{bmatrix} \begin{bmatrix} 0 \\ \theta \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\varphi & sin\varphi \\ 0 & -sin\varphi & cos\varphi \end{bmatrix} \begin{bmatrix} cos\theta & 0 & -sin\theta \\ 0 & 1 & 0 \\ sin\theta & 0 & cos\theta \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ \psi \end{bmatrix} = J^{-1} \begin{bmatrix} \varphi \\ \theta \\ \psi \end{bmatrix}$$

Equation 7

Where: φ, Θ, and ψ are the rotation of the vehicle fixed frames about the earth fixed x roll, y pitch and z yaw axes respectively. Inverting the function of J presents the desired Euler rate vector relationship of the system as;

$$\begin{bmatrix} \varphi \\ \theta \\ \psi \end{bmatrix} = J \begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} 1 & (sin\varphi\ tan\theta) & (cos\varphi\ tan\theta) \\ 0 & cos\varphi & -sin\varphi \\ 0 & \frac{sin\varphi}{cos\theta} & \frac{cos\varphi}{cos\theta} \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix}$$

Equation 8

The applied force F_b moment M_b of the system are the defined considering the relationship between the force of gravity Fg, drag force F_d, moment M_b, suspension forces and the four tyres as shown in the model below;

$$F_b = \begin{bmatrix} Fx \\ Fy \\ Fz \end{bmatrix} = \begin{bmatrix} Fdx \\ Fdy \\ Fdz \end{bmatrix} + \begin{bmatrix} Fgx \\ Fgy \\ Fgz \end{bmatrix} + \begin{bmatrix} Fexzx \\ Fexzy \\ Fexzz \end{bmatrix} + \begin{bmatrix} Fflx \\ Ffly \\ Fflz \end{bmatrix} + \begin{bmatrix} Frlx \\ Frly \\ Frlz \end{bmatrix} + \begin{bmatrix} Frrx \\ Frry \\ Frrz \end{bmatrix} \qquad \text{equation 9}$$

$$M_b = \begin{bmatrix} Mx \\ My \\ Mz \end{bmatrix} = \begin{bmatrix} Mdx \\ Mdy \\ Mdz \end{bmatrix} + \begin{bmatrix} Mgx \\ Mgy \\ Mgz \end{bmatrix} + \begin{bmatrix} Mexzx \\ Mexzy \\ Mexzz \end{bmatrix} + \begin{bmatrix} Mflx \\ Mfly \\ Mflz \end{bmatrix} + \begin{bmatrix} Mrlx \\ Mrly \\ Mrlz \end{bmatrix} + \begin{bmatrix} Mrrx \\ Mrry \\ Mrrz \end{bmatrix} + M_F \qquad \text{equation 10}$$

Where; F_{fl}, M_{fl} — Front left, F_{fr}, M_{fr} — Front right and F_{rl}, Mrl — Rear left, Frr, Mrr — Rear right

Non linear Slip model

This model will present the relationship between the force acting on the tyres, the vehicle dynamics considering the lateral, longitudinal, yaw rate and the slip angles respectively. Slip is defined as the force acting between the tyres and the ground when the vehicle is in motion. From the model of the vehicle dynamics, the forces acting on the tyres were defined using the tyres stiffness model in equation 4 and 5.

Thus for the front tyres, the slip is presented as sFL(t) and sFR(t) derived from the relationship between then force acting on the tyres in equation 4 and the slip angle (alpha Fj(t)) as shown in equation 11;

$$alpha\ \boldsymbol{F_j}(t) = delta\ (t) - \arctan(V_{y(t)+\frac{a(r(t))}{V_{x(t)}}}$$

Equation 11

For the rear tyres the force defined by equation 5 is considered to derive the slip sRL(t) and sRR(t), in line with the rear tire slip angle (alpha Rj(t)) to produce the resultant slip force as;

$$alpha\ \boldsymbol{R_j}(t) = \arctan(V_{y(t)+\frac{b(r(t))}{V_{x(t)}}} \quad \text{Equation 12}$$

In the designed models so far, beginning from equation (1 to 12) which can be collectively defined as the real time non linear structural dynamics of the autonomous vehicle in motion, with the nonlinearity induces using the slip model in equation 11 and 12. This model is represented as a nonlinear grey box identification structure of the autonomous vehicle under slip force using the equation below;

$$\text{AVUS} = \frac{dx}{dt} = F\ (t, u(t), x(t), p(n)) \quad \text{equation 13}$$

Where u(t) are the vehicle parameters which will be considered for feature extraction, p is the vehicle characteristics and x representing the lateral, longitudinal and yaw rate of the vehicle.

Feature extraction model

Feature extraction process is the real time collection of the non linear vehicle feature vectors as it moves and senses the least degree of slip force. This feature extraction model (Fxm) is designed using the relationship between the vehicle parameter defined in equation 13 as shown below;

$$\text{Fxm}\ (t) = \text{H}(t, u(n), x(t), p(t)) + \text{e}(t) \quad \text{equation 14}$$

When h is the height of the vehicle from the ground, u are the feature vectors which are the slip forces detected and sensed on the front (u1, u2) and rear tyres (u3, u4) and steering angle (u5) respectively.

Artificial neural network Model

After the feature extraction process, the feature vectors are feed to the neural network as a non linear auto regressive with external input model as shown below;

$$y(k+d)=N(y(k),y(k-1),\dots,y(k-n+1),u(k),u(k-1),\dots\dots u(k-n+1)) \quad \text{equation15}$$

Where u(k) is the feature vectors inputs, N is the non linear slip force, and y(k) is the system output as shown using the neural network architecture in figure 2.

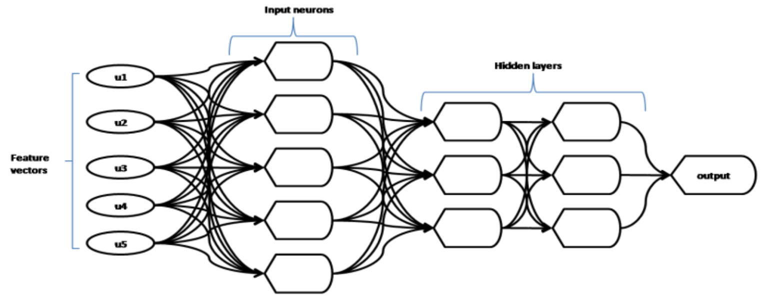

Figure 2: The neural network architecture

These nonlinear output parameters are trained using back propagation algorithm (see figure 3.4) to generate the approximate slip model as shown in equation 16;

$$\hat{y}(k+d)=f(y(k),y(k-1),\dots,y(k-n+1),u(k-1),\dots,u(k-m+1))+g(y(k),y(k-1),\dots,y(k-n+1),u(k-1),\dots,u(k-m+1))\cdot u(k)$$

equation 16

This approximate model is classified with the reference slip vector obtained from FCN LSTM dataset as shown in the structure;

$$u(k+1) = \frac{yr(k+d) - f[y(k),\dots,y(k-n+1),u(k),\dots,u\ (k-n+1)]}{g[y(k),\dots,y(k-n+1),u(k),\dots,u(k-n+1)]}$$

equation 17

The model of the trained normal vehicle structure in equation 17, is developed as an adaptive controller using the flow chart in figure 3, this model is classified with the approximate slip model to detect nonlinearity in the vehicle and hence control system (see training parameters in table 1).

Table 1; ANN training parameters

Parameters	values
Controller Training epochs	6
Size of hidden layers	6
No. delayed reference input	2
Maximum plant output	3.1
Maximum plant input	5
Number of non hidden layers	5
Maximum interval per sec	2
No. delayed controller output	1
No. delayed plant output	2
Minimum reference value	-0.05

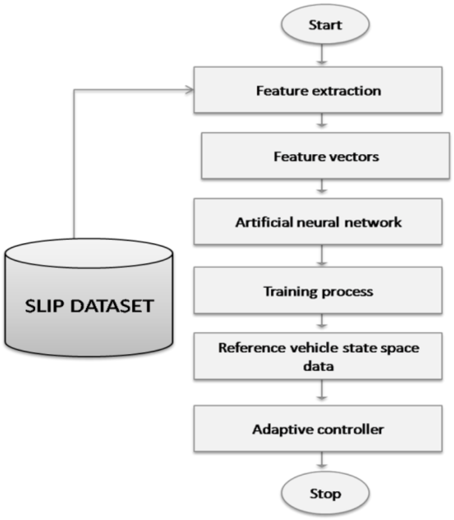

Figure 3: flow chart for controller

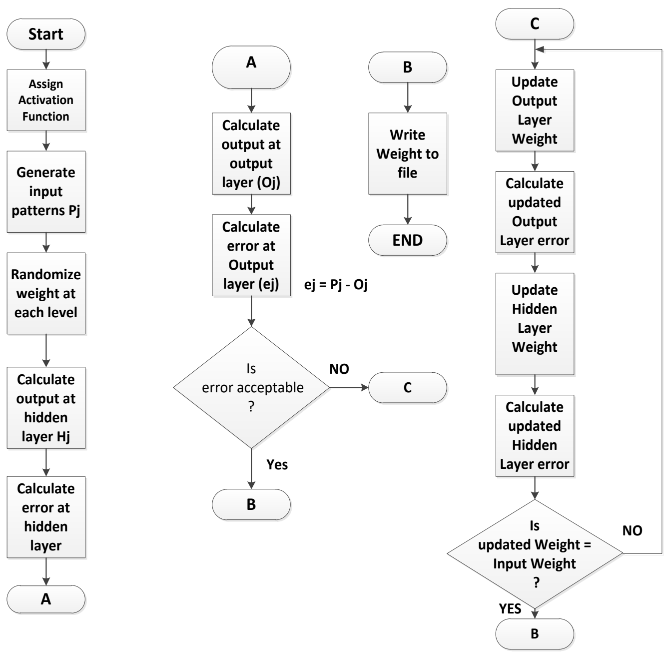

Figure 4: flow chart for Training algorithm

IV. IMPLEMENTATION

The system is implemented using the mathematical models designed in the previous section. The model portrays the designed the nonlinear vehicles structure redefined using the nonlinear grey box identification model in equation 13, relating the slip force, the vehicle dynamics and Newton law of motion. This slip is identified as a non linear regressive model using the equation 15, and trained using the neural network structure in equation 16 to control the vehicle using the adaptive controller designed in equation 17. The resultant simulink block which united this model is implemented using the neural network toolbox and control system toolbox as shown in figure 5;

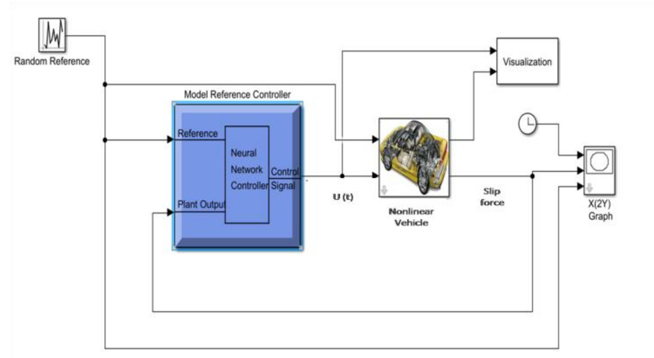

Figure 5: Control of the nonlinear vehicle

Table 2: Simulation parameters

Vehicle parameters	Value
Vehicle mass [kg]	1700
Distance from front axle to COG [m]	1.5
Distance from rear axle to COG [m]	1.5
Longitudinal tire stiffness [N]	150000
Lateral tire stiffness [N/rad]	40000
Longitudinal velocity [m/s]	17.60
Total drive time x and y distance [m]	300 x 150
Voltage	24V

V. RESULTS AND DISCUSSIONS

To evaluate the performance of the neural network training performance, the regression analyzer was used. The implication is due to its ability to analyze the training performance of the testing and training dataset respectively and collectively. From the result in figure 6, the regression analyzer shows the training performance of the slip dataset, and also that of the real time nonlinear vehicle data collected as a feature vector. The training performance produces a validation rate of 0.999; which indicated a training accuracy of 99%.

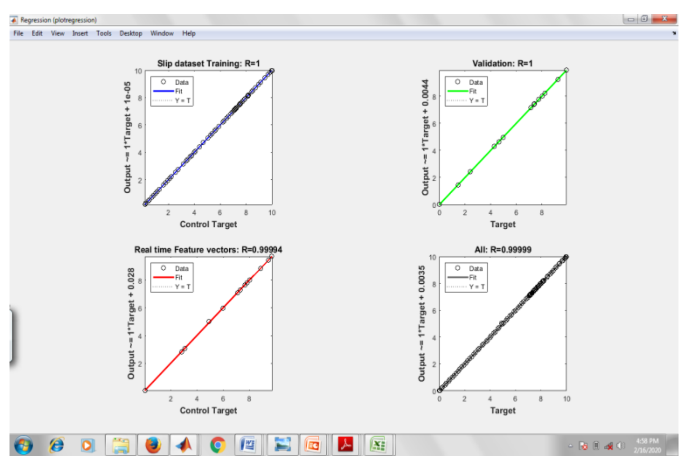

Figure 6: regression result of the training process.

The result shows that once nonlinearity is experience in the autonomous vehicle during translational motion, this is immediately detected and rectified using the necessary control structures.

The result in figure 7 also shows the relation between the validation, test and training process. From the mean square error performance, the best validation value is 5.8375e-10 at which the training was stopped. This shows a stable and précised training performance to justify the regression result obtained in figure 6.

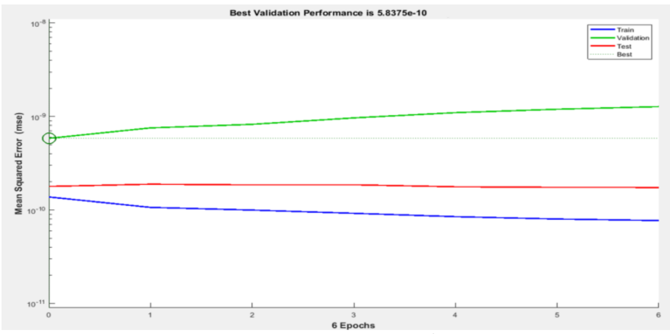

Figure 7: Mean square error performance

VI. CONCLUSION

This work has successfully developed a system which controls the nonlinear effect of slip on a translational autonomous vehicle using artificial neural network. The network is trained with a vehicle dataset collected form a moving vehicle at normal condition and used to classify real time autonomous vehicle nonlinear characteristics. These will immediate controls the vehicle dynamics once slip is identified and ensure smooth and steady state locomotive condition.

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