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Research Paper

INTELLIGENT PREDICTION AND PREVENTION OF VEHICLE ROLLOVER USING NNLQG REGULATOR

Binda M B[1]* and M Rajaram[2]

*Corresponding Author: Binda M B, ✉ bindamb@gmail.com

In this paper, we present a noval methodology for prevention of vehicle rollover model which is suitable for preventing the rollovers that was caused in many vehicles. For vehicles that are predicted to be susceptible to wheel-lift off, various control mechanisms are implemented by earlier researchers. In this work, we propose a neural network based method for preventing and predicting the rollover based on the combination of Neural networks logic with Gaussian controller which does not require such accurate information about the vehicle. The validity of the proposed methodology is proved by the experimental results and it is used to realize rollover prevention in the direction of the rollover. The primary assumption in this implementation is that the vehicle is equipped with a conventional neural network based controller system.

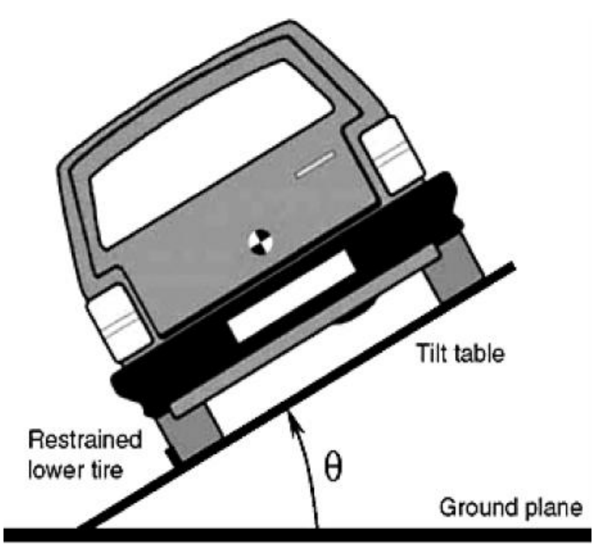
Keywords: Rollover, Neural network tuned PID controller, PID controller

INTRODUCTION

It is already known that the vehicles with a high center of gravity such as vans, pickups, and the highly popular Sport Utility Vehicles are more prone to rollover accidents. According to the 2004 data (Technical Report, 2006), light trucks such as pickups, vans and SUV's were involved in nearly 70% of all the rollover accidents in the world in which the SUV's alone responsible for almost 35% of this total. The major fact of the current automotive fleet in the world consists of nearly 56% pickups, vans and SUV's (Runge, 2003), along with the recent increase in the popularity of SUV's worldwide, makes rollover an important safety concern. There are two major categories of vehicle rollover that could be caused in these vehicles they are tripped and un-tripped rollover. A tripped rollover commonly occurs when a vehicle slides sideways and digs its tires into soft soil or strikes an object such as a curb or guardrail. Driver induced un-tripped rollover can occur during typical driving situations and poses a real threat for top-heavy vehicles. A schematic representation of rollover model is shown in Figure 1.

1 Research Scholar, Sathyabama University, Chennai, India.
2 Vice Chancellor, Anna University, Chennai, India.

Figure 1: A Vehicle Rollover Model



Examples for causing these sort of rollovers are excessive speed during cornering, obstacle avoidance and severe lane change maneuvers, where rollover occurs as a direct result of the lateral wheel forces induced during these maneuvers. In recent years, rollover problem has been the interesting subject of intensive research for various researchers. This research is geared towards the development of major rollover prediction schemes and occupant protection algorithms. It is however, possible to prevent such a rollover incident by monitoring the vehicle dynamics and applying proper control effort ahead of time. Therefore there is a need to develop vehicular assistance technologies which would be transparent to the driver during normal driving conditions, while acting in emergency situations to recover handling of the vehicle until the driver recovers control of the vehicle.

This paper seeks to contribute significantly to the rollover prevention methods that directly modify the driver's steering command in a way such that the driver does not realize the effect of the controller. However, in order to properly accomplish this goal, the main features behind vehicle rollover must first be understood. In this paper a robust rollover prevention controller methodology based on the combination of neural network and LQG regulator is proposed in order to prevent the vehicular rollover. The proposed control design is an application of recent results on the design of control systems which guarantee that the values of the performance outputs of a vehicle do not exceed certain thresholds when subject to different neural networks.

RELATED WORK

Rollover prevention is a topical area of research in the automotive industry and various research studies have been published recently as shown in the literature. Relevant literatures include Palkovics *et al.* (1999), at which they proposed a novel methodology called Roll-Over Prevention (ROP) system for the purpose of using it in commercial trucks making which uses the wheel slip difference logic on the two sides of the axles to estimate the tire lift-off which is prior to the rollover.

Wielenga (1999) suggested the ARB (Anti Roll Braking) system utilizing braking of the individual front wheel outside the turn or the full front axle instead of the full braking action. The suggested control system is based on lateral acceleration thresholds and/or tire lift-off sensors in the form of simple contact switches.

Chen and Peng (2001) suggested using an estimated Time To Rollover (TTR) metric as an early indicator for the rollover threat. When TTR is less than a certain preset threshold value for the particular vehicle under interest, they utilized differential braking to prevent rollover.

Ackermann and Odenthal (1998) and Odenthal *et al.* (1999) proposed a robust active steering controller, as well as a combination of active steering and emergency braking controllers. They utilized a continuous-time active steering controller based on roll rate measurement. They also suggested the use of a static Load Transfer Ratio (LT Rs) which is based on lateral acceleration measurement; this was utilized as a criterion to activate the emergency steering and braking controllers.

ROLLOVER PREVENTION METHOD BY NNLQG REGULATOR

In this paper, a Neural Network based Linear Quadratic Gaussian (NNLQG) controller was proposed. The Neural Network based Linear Quadratic Gaussian (NNLQG) controller design for the rollover model mostly focuses on three parts based on the basic principle of the basic LQG controller mentioned above: (1) optimal Linear Quadratic Estimator (LQE) design; (2) optimal Linear Quadratic Gaussian Regular (LQR) design; (3) system integration along with the Neural Network. Together with the linear quadratic estimator and the Linear Quadratic Gaussian Regular (LQR), the Neural Network solves the problem of linear-quadratic-Gaussian control. Figure 2 shows the architecture of the NNLQG system.

LQG Optimal Controller

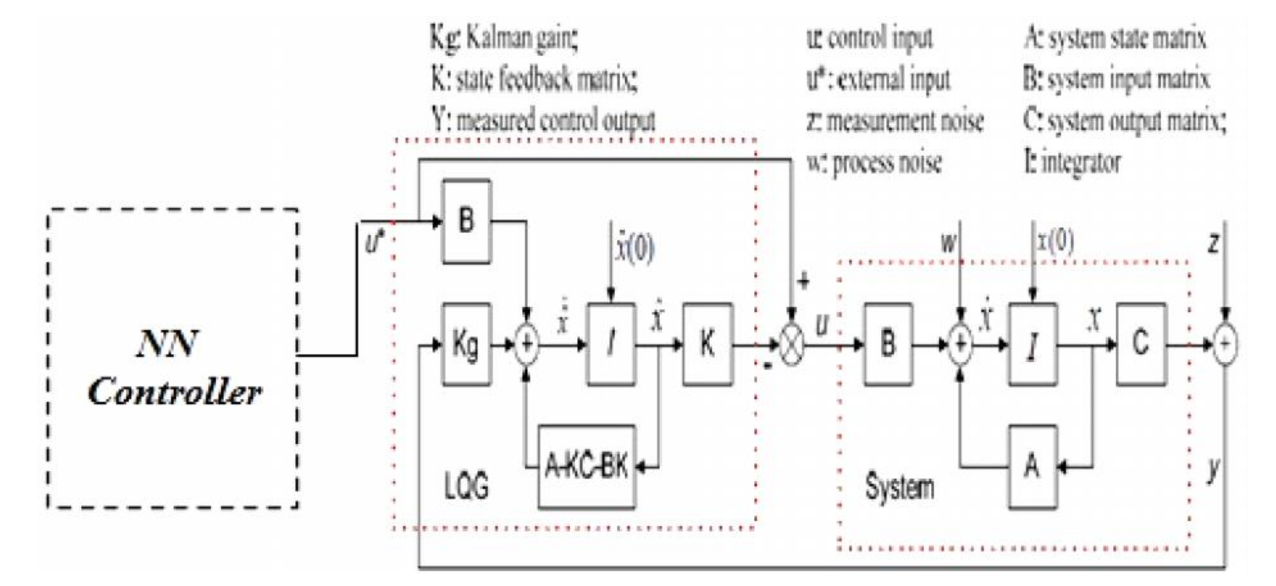
The LQG control signal u is a state feedback described below:

$$u = -Kx \quad ...(1)$$

where, the K vector is derived from the solution of a Riccati Algebraic Equation. u can be derived from the minimization of the quadratic cost function:

$$J = \sum_{k=0}^{\infty}[x^T(k)q_c(k)x(k) + u^T(k)r_c(k)u(k)] \quad ...(2)$$

Figure 2: Architecture of Proposed NNLQG System



where $q_c(k)$ and $r_c(k)$ are the weight matrices, i.e., design parameters chosen to meet the desired closed loop performance is a general quadratic cost function which not only state excursions but control excursions and state-control products as well. This equation plays a significant role in designing linear optimal controller.

Design of a Neural Network Based Linear Quadratic Estimator

The Kalman filter is a feasible estimation approach that can fuse multiple sensory measurements to provide relatively accurate results. The Kalman filter can minimize the mean of the squared error from a series of noisy measurements. In this proposed methodology, recurrent neural network based controller topology is used to control the flow of executions that are fed towards the Kalman filter present in the LQG. The steps for controlling and fedding the input to the estimator is as follows:

NEURAL NETWORK

Recurrent Neural Network (NN) is a recurrent discrete-time network with S input units, X internal units, and Y output units. NN is recurrent in nature with a non-trainable sparse recurrent part and a simple linear read out. The training and testing neural network is to map the input pattern with target output data. For this purpose, the inbuilt-in function has to prepare a network table and finally a set of numbers are stored. During testing, the network function is used to test the pattern.

In this NNLQG controller, the membership values generated in the network table is fed as input towards the normal LQG in order to reduce the flow of executions.

Training Neural Network for Prediction

Step 1: Read the pattern (quadratic Gaussian and its target value).

Step 2: Create network function based on the patterns.

Step 3: Match the network values with the controller values.

Step 4: Process with target values.

Step 5: Obtain final values.

Testing Neural Network for Prediction

Step 1: Input a target (rollover) values.

Step 2: Process with network function.

Step 3: Find the Gaussian value to which the pattern belongs.

Step 4: Obtain estimated target values.

Step 5: Classify and predict the rollover.

Design of NN Linear Quadratic Regulator

Optimization Method: The control strategy is characterized by the control configuration illustrated in Figure 2. The realization of the optimal control strategy depends on the state estimation and the control law. Considering the roll model control problem, the control law is optimized by minimizing the cost function to guarantee control objectives which are a minimal position error and using as little control effort as possible.

Control Law: The control values can be obtained by the optimization method mentioned above. In order to calculate this, the steepest descent method was applied, which is an iterative method, being simple implementation, but with slow convergence.

Calculation and Simulation Results: The Matlab codes were made and simulation has been conducted to (1) select the controller's parameters, like the cost function's sensitivity to dynamic effects and the stop criterion, (2) obtain the cost function and the control law. The cost function has been close to zero after 5 iterations.

System Integration: System integration is a significant step in designing NNLQG controller after designing the optimal estimate and configurating the optimal controller. Figure 3 shows the system closed-loop configuration.

Figure 3: System Closed-Loop Configuration

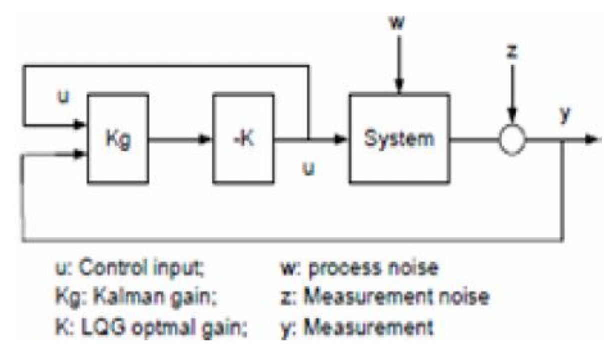


Figure 4: Simulink Model

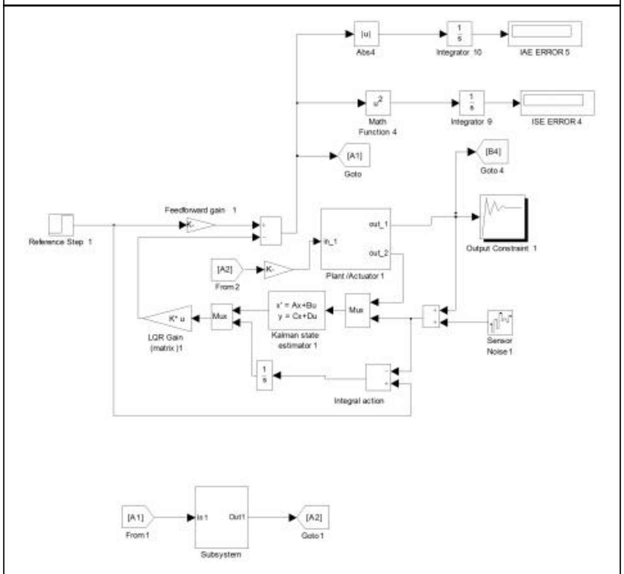
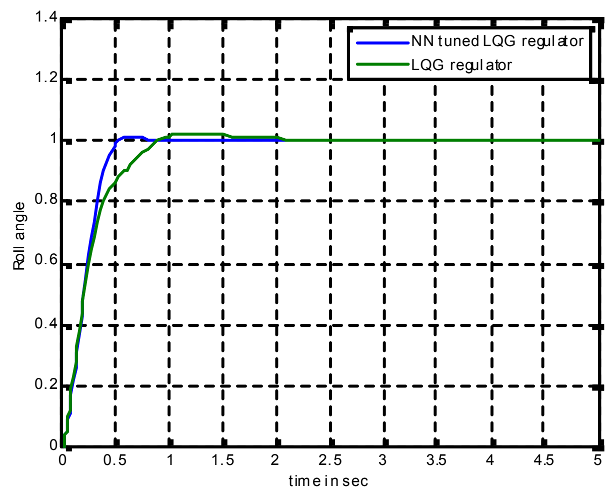


Figure 5: Roll Angle Response for 3 DOF Vehicle Model



SIMULATION RESULTS

In order to verify the proposed mitigation control, simulation tests are conducted and the simulink model for the test is shown in Figure 4.

From Table 1, and also observing the figure 5,we can conclude that NN self tuned LQG Regulator is very much better, neglecting the overshoot in the response and has a very low settling time and rise time compared to LQG Regulator.

Table 1: Results of LQG Controller and NN self Tuned LQG Controller for a 3 DOF Vehicle Model

Measuring Factors	LQG Controller	NN Self Tuned LQG Controller
Rise Time in sec	0.7	0.3
Maximum Overshoot in %	1	0.004
Settling Time in sec	4	0.8

CONCLUSION

The main purpose of this research work is to propose a novel methodology for preventing rollover when a vehicle may be at risk for wheel-lift. Additionally, multiple control strategies such as neural network and LQG controllers were combined in order to control the vehicle rollover. To investigate the vehicle transient and steady states, an improved rollover model combined with the neural network topology was established in this study. An optimal controller for a rollover model has been combined with the neural controller which is designed in Matlab simulation to implement a predictive control to the vehicle roll over.

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APPENDIX

Nomenclature

Parameters	Definition
$\neg_x$	Longitudinal velocity (body-fixed frame)
μ_r	Yaw rate (angular rate about vertical axis)
m	total mass of the vehicle
I_{zz}	Inertia about the vertical axis
a	front-axle-to-CG distance
b	rear-axle-to-CG distance
L	Track of vehicle
t	Width of vehicle
	Side Slip angle of the vehicle body
k_1	Front cornering stiffness
k_2	Rear cornering stiffness
¤	roll angle
μ_r	yaw acceleration
I_z	Inertia about the yaw moment
$\sim_1$	slip angles of front tires
$\sim_2$	slip angles of rear tires
h_0	height of the vehicle's Center of Gravity (CG) standing above the ground level
h	distance between the vehicle CG and the assumed roll axis
T	width of the vehicle track
Δh and ΔT	deformation of suspension and tire
k_Φ	total roll stiffness
c_Φ	total roll damping of suspension
I_x	roll moment of vehicle inertia

Parameters	Values	Parameters	Values
m	1030 Kg	b	1.56 m
I_{yy}	1705 Kg-m^2	L	1.4 m
m_s	825 Kg	h	0.52 m
I_{xx}	375 Kg-m^2	k_1	–45500 N/rad
I_{xz}	72 Kg-m^2	k_2	–76650 N/rad
I_{zz}	1850 Kg-m^2	$k_{..}$	53000 N-m/rad
a	0.93 m	$C_{..}$	6000 N-m-sec/rad^2