Thesis for the Master of Science

# Estimation of Vehicle Roll Angle and Road Bank Angle Using Deep Neural Network

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February 2019

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**Estimation of Vehicle Roll Angle and Road Bank Angle Using Deep Neural Network**

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A Theis submitted to the graduate school of Hanyang University in partial fulfillment of the requirements for the degree of *Master of Science*.

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February 2019

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This thesis, written by *Tae Hui LEE,*
has been approved as a thesis for the *Master of Science*

February 2019

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Graduate School of Hanyang University

*For my beloved family*

# Abstract

**Estimation of Vehicle Roll Angle and**
**Road Bank Angle Using Deep Neural Network**

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In the vehicle driving situation, a road bank angle affects not only the vehicle roll dynamics but also the vehicle stability. For more stable and safe driving, accurate and reliable estimation of vehicle states is critical. Conventional road bank- angle estimation methods typically employ a dynamic filter compensation which is quite accurate in estimating the steady-state driving conditions. However, in unstable driving conditions such as high-speed driving, it is not reliable much.

The purpose of this research is proposing a novel method estimating vehicle roll angle and road bank angle using a deep neural network(DNN). In order to estimate the vehicle roll angle and road bank angle, among widely used vehicle onboard sensors, input data from five sensors are selected. The proposed deep neural network is trained using the input data acquired in various driving situations.

In this research, data acquisition process and verification of estimation algorithm are conducted by simulation using a commercial vehicle model. The vehicle driving simulation and vehicle sensor data acquisition are accomplished by IPG Carmaker, which is one of the most well-known vehicle simulation tools. Modeling and training of the DNN model are results are accomplished by Keras in Python.

Results show that the performance of the proposed method using the DNN is more accurate in both vehicle roll angle and road bank angle estimations than conventional methods. Especially, the proposed method reveals a notable performance enhancement in the road bank angle estimation.

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# Chapter 1 Introduction

## 1.1 Research background and objectives

A vehicle rollover crash is known that much more likely to result in fatalities than other crashes. According to the National Highway Traffic Safety Administration (NHTSA), in all vehicle crashes in 2010, only 2.1% involved a rollover. However, rollover accounted for nearly 35% of all death from vehicle crashes [1]. For this reason, a vehicle roll control system and rollover index(RI) has been developed [2]. A Roll control system(RSC) based on RI prevents vehicle rollover and improve lateral stability [3].

However, the direct measurement method of vehicle roll angle and road bank angle using DGPS sensors is too expensive to apply to commercial vehicles. Therefore, for the improvement of roll control performance, precise estimation of vehicle state data by using sensors of affordable price is important.

This research focuses on the estimation of two states. One is vehicle roll angle. Another is a road bank angle, which directly affects vehicle roll angle.

Vehicle roll angle estimation has been mostly researched using a vehicle model-based closed-loop estimator [4-6]. These researches mainly used some kinds of Kalman filters. However, they are vulnerable to some kinds of driving scenarios depending on the applied vehicle model. Moreover, most of them suppose roads without bank angle, which is difficult to apply in some real roads.

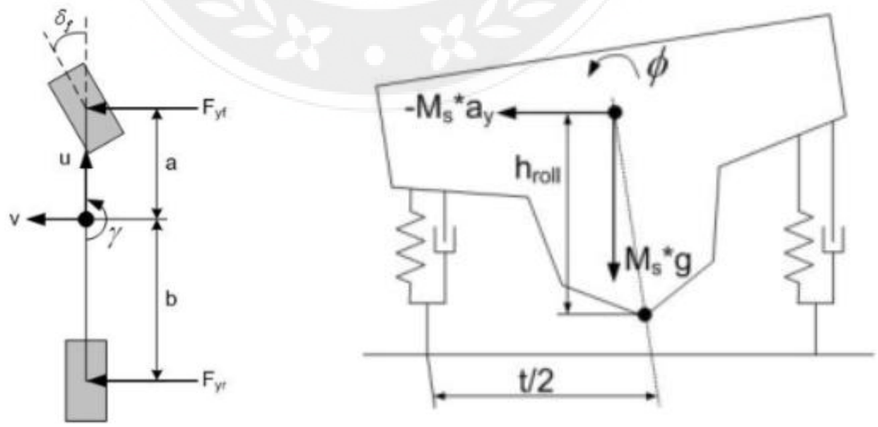
Road bank angle estimation research has been researched with many control methods. A dynamic filter compensation method, H. Tseng proposed [7] is one of the most influential research in those methods. But it doesn't fit well with unstable driving conditions.

In order to overcome these problems, this research proposes a vehicle roll angle and road bank angle estimation method using the deep neural network. The proposed method can estimate two states at the same time which can be applied to roads with bank angle and without a bank angle. Sensors data acquired from various driving scenarios which make its performance more robust than former methods.

In this research, vehicle roll angle estimation performance was compared with the existing vehicle lateral dynamics-based extended Kalman filter model. Road bank angle estimation performance was compared with the existing dynamic filter compensation model which is Tseng proposed. The performance was verified with a simulation.

## 1.2 Related works

There has been much research about vehicle roll angle and road bank angle estimation. Vehicle roll angle estimation method can be classified into using lateral acceleration data, directly integrating roll rate, using the measurement of chassis displacement, vehicle model based Kalman filter method etc. [5] In [2], a rollover index(RI) was suggested. As an increasement in rollover danger, the RI proposed to prevent rollover by vehicle control. [3] proposed vehicle lateral dynamics and roll model-based roll estimator. Nonlinear model using Extended Kalman filter presents a reasonable estimation performance on a normal highway driving situation. However, because of the vulnerability on a rough terrain or off-road driving situation, which have road disturbances, the research [9] proposed. In the research, a model-based roll state estimator was designed with the fusion of vehicle lateral dynamics model and the vertical dynamics model.




(a) 2DOF bicycle model (b) Vehicle model before a wheel-lift-off condition

**Fig. 1-1 Vehicle model for lateral dynamics based roll estimator (R. Chung et al.)[4]**

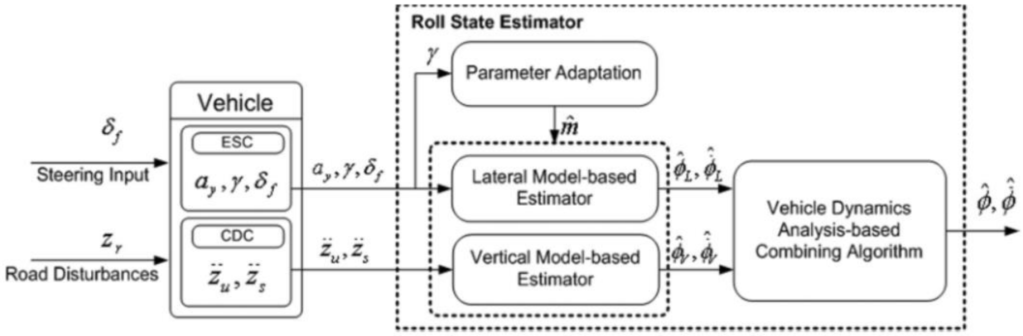



**Fig. 1-2 Schematic of the model-based roll state estimator (J. Yoon et al.)[3]**

There are difficulties to estimate road bank angle because of the hardness to differentiate between road disturbance component from vehicle lateral dynamics component. Tseng proposed Dynamic compensation filter(DFC) method to estimate road bank angle [7]. It assumes steady-state values of the transfer function in the formula. So, it performs worse in an unsteady driving situation as high-speed driving. After this research, [10] proposed an estimation method using a disturbance observer, [11] proposed a method using an adaptive control theory. [8] presented a proportional-integral H-infinity filter(PIF) based road bank angle estimation method.

$$\boldsymbol{sin\widehat{\varphi}_{dyn} = sin\widehat{\varphi}_v \times max[0, 1 - |DFC| - |dsin\,\widehat{\varphi}_v/d\,t|]}$$

$$\boldsymbol{DFC = H_{\varphi \circledR a}(sin\widehat{\varphi}_a - sin\widehat{\varphi}_v) + u \times H_{\varphi \to a}(sin\widehat{\varphi}_r - sin\widehat{\varphi}_v)}$$
$$\boldsymbol{= \frac{-gL}{L + ku^2}(sin\widehat{\varphi}_a - sin\widehat{\varphi}_v) + \frac{gku^2}{L + ku^2}(sin\widehat{\varphi}_r - sin\widehat{\varphi}_v)\Big)}$$

**Fig. 1-3 DFC method (H. Tseng)[7]**

## 1.3 Research scope

The purpose of this research is to estimate the vehicle roll angle and road bank angle simultaneously. The driving scenario was designed to efficiently validate two states. The vehicle driving situation was limited to four high-speed driving, which classified to 20% road bank angle road with 70kph target velocity, 30% road bank angle road with 70kph target velocity, 20% road bank angle road with 100kph target velocity, 30% road bank angle road with 100kph target velocity.

**Fig. 1-4 Vehicle roll**

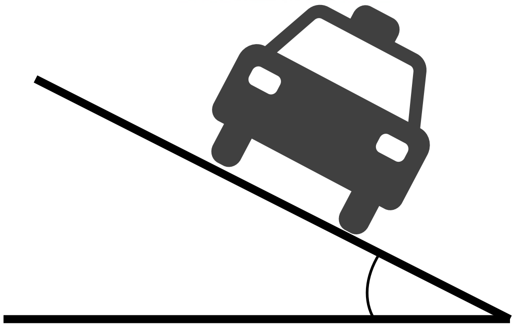


**Fig. 1-5 Vehicle on the banked road**

## 1.4 Outline

This paper is written in the following manner. Chapter 2 presents the system architecture and its details that are proposed in this research. Chapter 3 describes and explains some techniques used for designing the deep neural network model for states estimation. Chapter 4 describes how the simulation for validation processed, analyze its results. Finally, in chapter 5, finalize the paper with a conclusion.

# Chapter 2 System Architecture

Fig. 2-1 shows the system architecture of our proposed model. The vehicle sensor data are acquired from five vehicle onboard sensors. Five vehicle onboard sensors data are longitudinal velocity, steering angle, vertical acceleration, yaw rate and lateral acceleration which are widely accepted in a control area network (CAN).

The dataset from the various driving situation can be used to train the DNN module. The DNN module estimates the vehicle roll angle and the road bank angle at the same time.

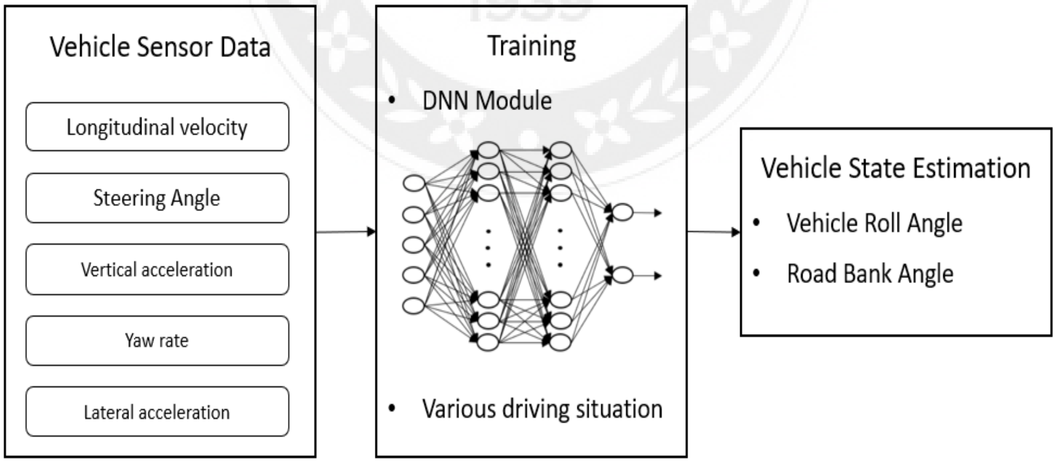



**Fig. 2-1 Overall system architecture**

## 2.1 Input selection

Among various vehicle onboard sensor, five sensor data are selected. The input selection is based on the existing vehicle lateral dynamics model-based roll estimator and the Tseng model [4, 7]. The bicycle model-based roll estimator used steering angle, yaw rate, and lateral acceleration data as an input. Meanwhile, the Tseng model needs a yaw rate, steering angle, lateral acceleration, and longitudinal velocity. Vertical acceleration data, which is directly affected by the road bank angle, is additionally included.

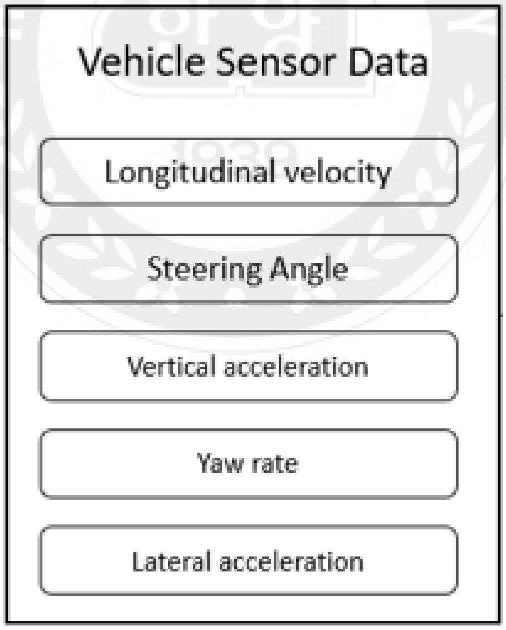



**Fig. 2-2 Selected Inputs**

## 2.2 Feed-forward Neural Network

This research used a multi-layer feed-forward(MLF) neural network as a deep neural network(DNN) model. In artificial neural networks(ANN) there is two main types of training process: supervised and unsupervised training. MLF neural networks are the simplest and most popular kind of neural network in supervised learning [12]. Fig. 2-3 shows an outline of the MLF neural network model used in this research.

The MLF neural network consists of neurons. All neurons belong to layers, which is classified into the input layer, hidden layers, and output layer. In each neuron, inputs are fed to outputs through a series of weight. In that process, there is an activation function, the function that changes the sum of signals of inputs to outputs. The process and expression of activation function are shown in Fig. 2-4 and Eq. (2-

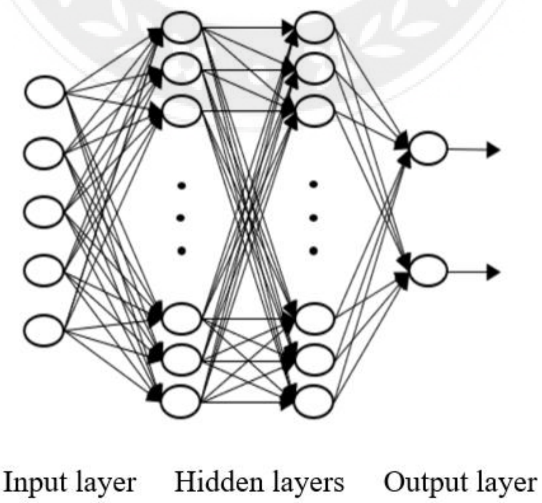



**Fig. 2-3 Feed-Forward Neural Network**

1). Neurons with the activation function are called artificial neurons. There are some well- known activation functions as sigmoid function, tanh function, rectified linear unit(ReLu) etc. Graphs of activation functions are shown in Fig. 2-5. It is mostly used in neural-network applications. In this network, data move in one direction, from the input layer to the output layer.

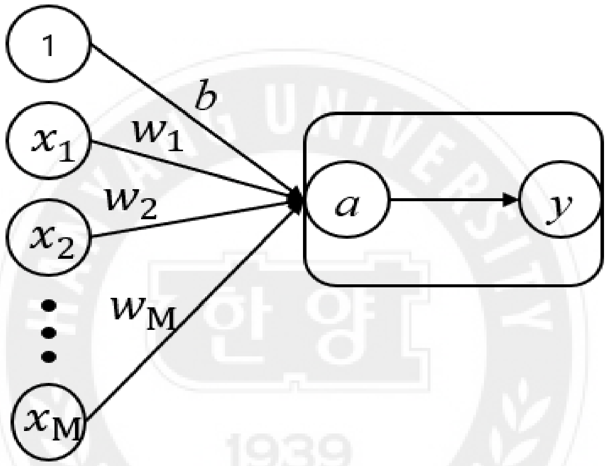



**Fig. 2-4 Process of an activation function**

$$y(x,w) = f\left(\sum_{j=1}^{M} w_j x_j + b\right) \tag{2-1}$$

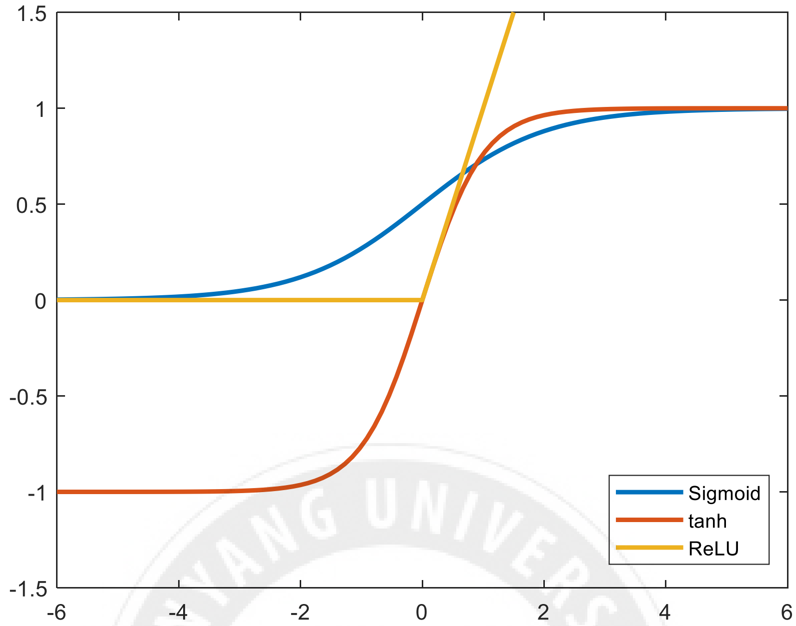



**Fig. 2-5 Graphs of activation functions**

# Chapter 3 Deep Neural Network Model

## 3.1 Deep Neural Networks(DNN)

Deep neural networks are one of the techniques in a deep learning. Deep learning is a kind of machine learning which makes computers possible to learn from data and understand the world in terms of a hierarchy of concepts [13].

DNN belongs to artificial neural networks(ANN) which consist of many hidden layers between an input layer and an output layer [14]. Therefore, they are effective for modeling complex non-linear systems. Moreover, they can model complex systems by fewer units compared to similarly modeled ANN.

A previous ANN had many problems. There were overfitting problems due to training data, gradient vanishing in using a sigmoid function, hardware problem because of an increment of computation load etc. These problems were improved in many ways such as a proposal for new initialize point algorithms, activation functions, dropout algorithms, hardware performance improvement etc. Therefore, it could be possible to add many layers in the ANN, which is called DNN.

DNN was mainly researched by feed-forward neural networks, but recent researches apply DNN in recurrent neural networks(RNN) and convolutional neural networks(CNN).

## 3.2 Deep Neural Network Structure

The proposed DNN model consists of four layers including two hidden layers. As an activation function, a scaled exponential linear unit (SELU) is adopted. In each layer, the DNN model initializes weight randomly by a normal distribution. In order to avoid an overfitting problem, the model randomly selects inputs and applies a dropout technique. The detailed structure of the proposed DNN model is shown in Fig. 3-1. The proposed model is designed by the Keras, an open source neural network library written in Python with TensorFlow backend.

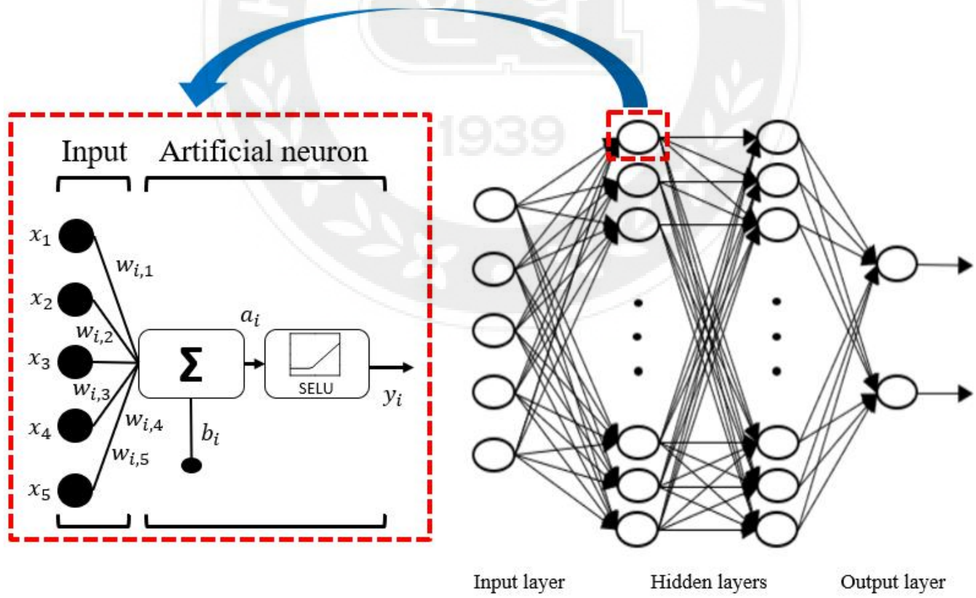



**Fig. 3-1 Proposed Deep Neural Network Structure**

## 3.3 Scaled Exponential Linear Units(SELU)

Deep learning has developed much via convolutional neural networks(CNN) and recurrent neural networks(RNN). However, models with standard feed-forward neural networks(FNN) are hard to find.

As layers of neural networks deeper and more complex, to robustly train deep neural networks, batch normalization technique is adopted. The reason why a deep FNN performance is not good is that as layers go deeper, FNN trained with normalization techniques suffer from perturbations and have high variance in the training error, while both RNN and CNN are less prone to these perturbations.

Therefore, the Self-normalizing neural networks (SNNs), was introduced [15]. It is the neural networks that the activation function called scaled exponential linear units(SELU) is applied. By applying the SELU as an activation function to

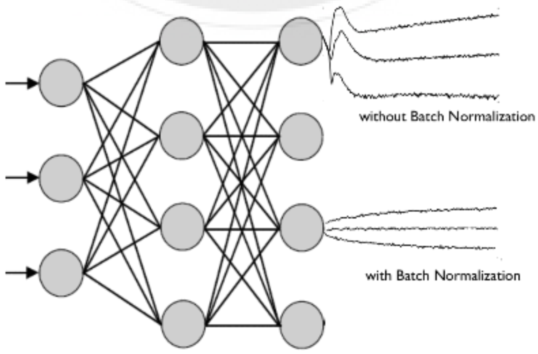



**Fig. 3-2 Batch normalization**

networks, explicit normalization techniques like the batch normalization don't need anymore. In the SNN, the normalization occurs inside the activation function as training.

The expression and the graph of SELU are shown below. For standard scaled inputs which is zero mean and one deviation, the values of $\alpha \approx 1.67$, $\lambda \approx 1.05$.

$$selu(x) = \lambda \begin{cases} x & if\ x > 0 \\ \alpha e^{x} - \alpha & if\ x \leq 0 \end{cases} \tag{3-1}$$

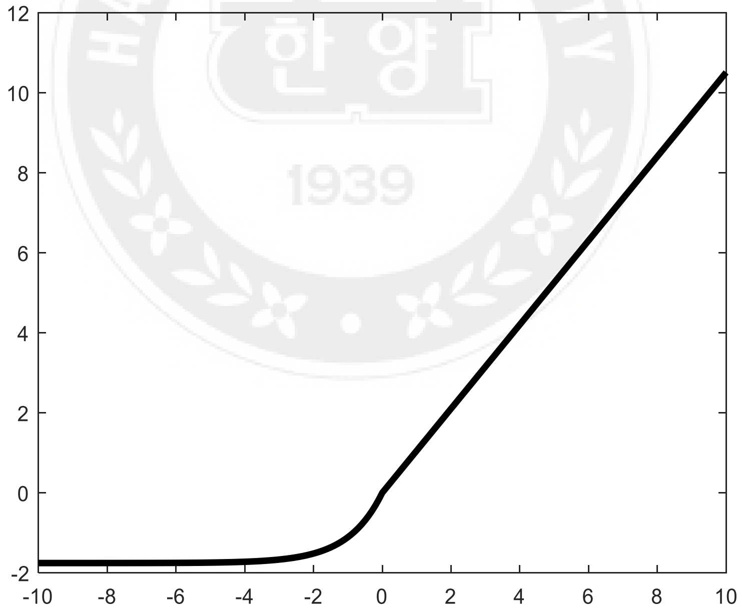



**Fig. 3-3 The graph of SELU**

The normalization properties of SNN make training deep networks with many layers, networks more robustly during training. Therefore, we can suppose that a deep FNN which SELU is applied can make a more robust and better performance than a normal FNN with many layers.

## 3.4 Dropout

As parameters in deep neural networks increase and training data are not enough, an overfitting becomes a serious problem. Overfitting means that a model is trained with training data too well, so not fit well with new data.

Therefore, the dropout technique to solve the overfitting problem was introduced [16]. Dropout is a technique that deletes neurons during training. Deleted neurons do not deliver signals to neurons in the next layer. During training, when data passing, it selects neurons that would be deleted, when testing it pass signals to all neurons. While when testing, it generates output by multiplying the deleted ratio of training to outputs of neurons.

Therefore, in this research, to prevent overfitting, the dropout technique is applied to every layer. The overall outline of the dropout is shown below.

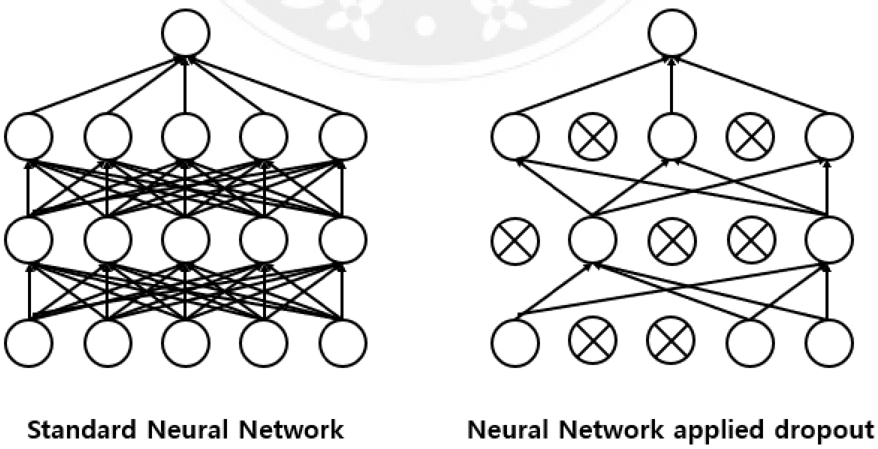



**Fig. 3-4 Dropout**

# Chapter 4 Simulation Verification

## 4.1 Simulation process

Sensor data are acquired from driving simulations of IPG Carmaker 310 product examples. The Carmaker is a simulation solution for testing passenger cars and light-duty vehicles [17]. It has about 310 kinds of product examples, which are different driving scenarios. Some of them are scenarios with a banked road, some are not. This research used 265 examples of them, which exclude inappropriate examples for training. Total driving distance of examples is about 363.6km, time is about 5.6hour.

The DNN module is designed and trained by the Keras by Tesorflow backend in Python. Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano [18].

The overall simulation process is as follows. In various example scenarios, five vehicle onboard sensor data are acquired with a constant target velocity, which is 100kph. Sensor dataset is used as input in a DNN module for training. The trained DNN module estimate two states at the same time, vehicle roll angle and road bank angle. The overall simulation process is shown on the next page.

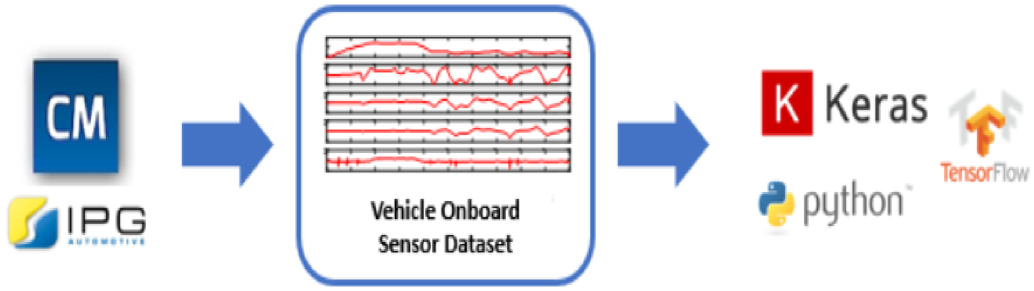



**Fig. 4-1 Simulation process**

## 4.2 Test driving scenario

A test driving scenario is modeled to effectively verify vehicle roll angle and road bank angle together. It includes a road with an angled bank and a curved road without a bank.

The test scenario is as follows. The vehicle starts from the top-left corner. It speeds up with straightly driving and enters a road with bank angle. The banked road affects vehicle roll angle. So, in this course, we can verify the vehicle roll angle and the road bank angle estimation performance. The radius of the road is set as 100m.

After getting out of the banked road, the vehicle enters the curved road without bank angle. Driving in the curved road affects vehicle affects vehicle roll angle, while the bank angle is still zero. So, we can verify the vehicle roll angle estimation performance and an error of the road bank angle estimation in this course.

This research implemented a test driving many times in this course. Every time conducted the test, the bank angle and vehicle target velocity was different.

The overall scenario is shown below.

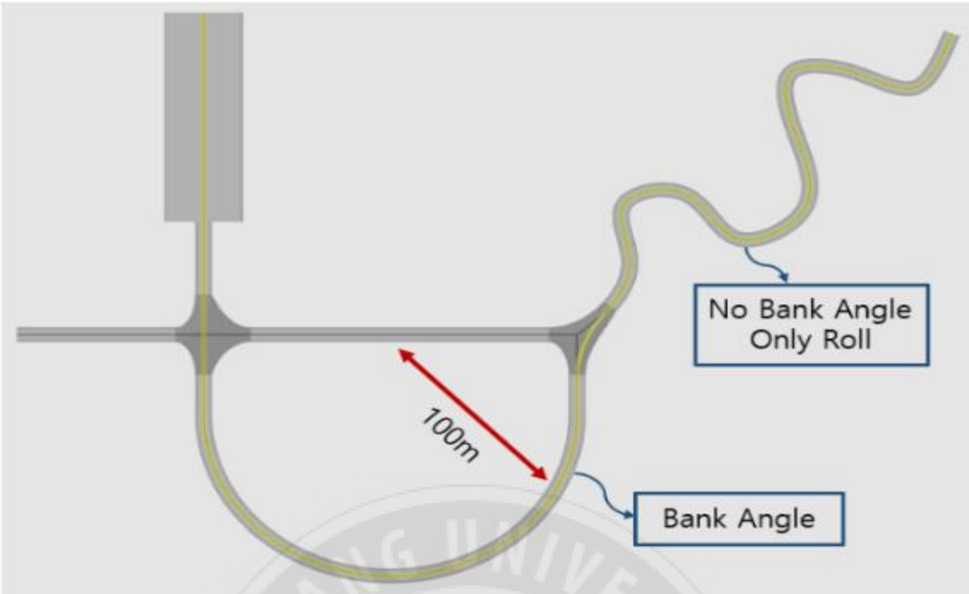



**Fig. 4-2 Test driving scenario**


**Fig. 4-3 Driving on the banked road**


**Fig. 4-4 Driving on the curved road without bank angle**

## 4.3 Simulation results

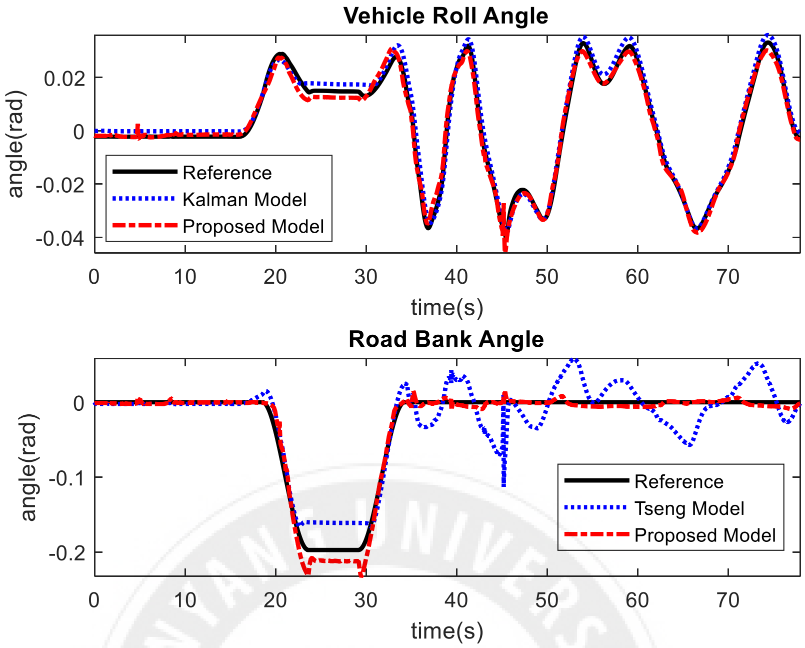
The simulations were conducted on the test scenario with six different conditions to verify the performance of the proposed model. Six conditions are composed of three kinds of target velocity: 70kph, 100kph, 130kph, and two different road bank angle: 20%, 30%.

Upper-side graphs show the reference value of vehicle roll angle and estimated values of vehicle roll angle. Among estimated values, a blue line presents Kalman estimator value a based on lateral dynamics vehicle model, which was introduced in related works. A red line presents the estimated value of the proposed model.

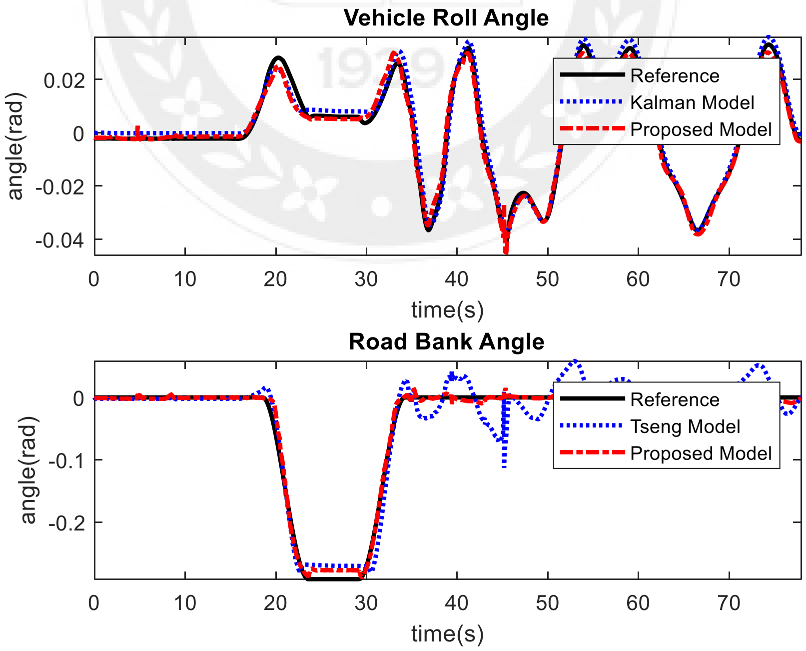
The lower-side graphs show the reference value and estimated values of road bank angle. Similarly, a blue line shows the DFC model which is proposed by Tseng. It was also introduced in related works. An estimated value of the proposed model was presented by a red line.

In vehicle roll angle estimation value, it looks like the estimation performance of the comparison model and the proposed model are both reasonable. But the roll angle represented in this graph put the reference zero degrees on the road. Therefore, we can predict that the estimation performance of the comparison model would not be fit well consider of the banked road.

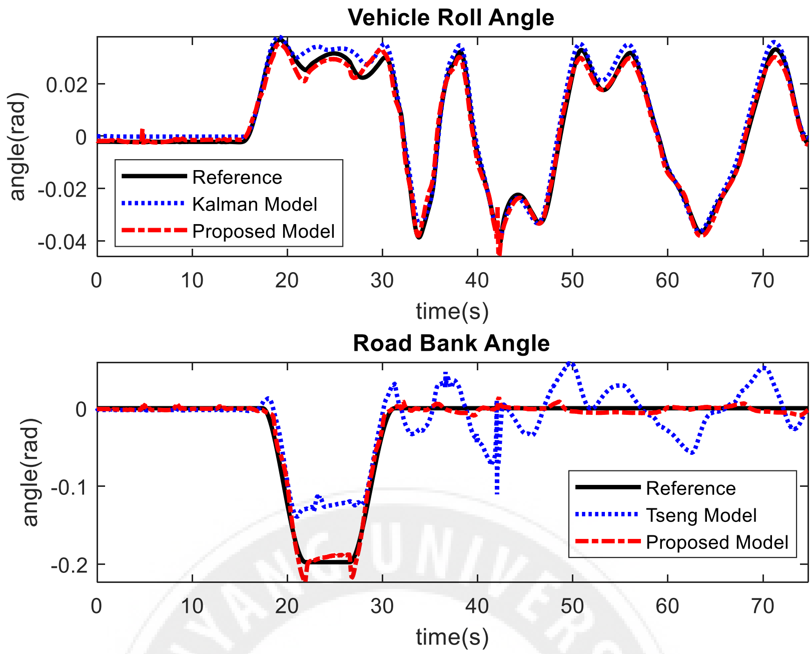
On the other hand, graphs of road bank angle estimation show that definite performance difference of the model proposed by Tseng and proposed in this research. Most simulations show that the estimation performance of the proposed model is better than the comparison model.



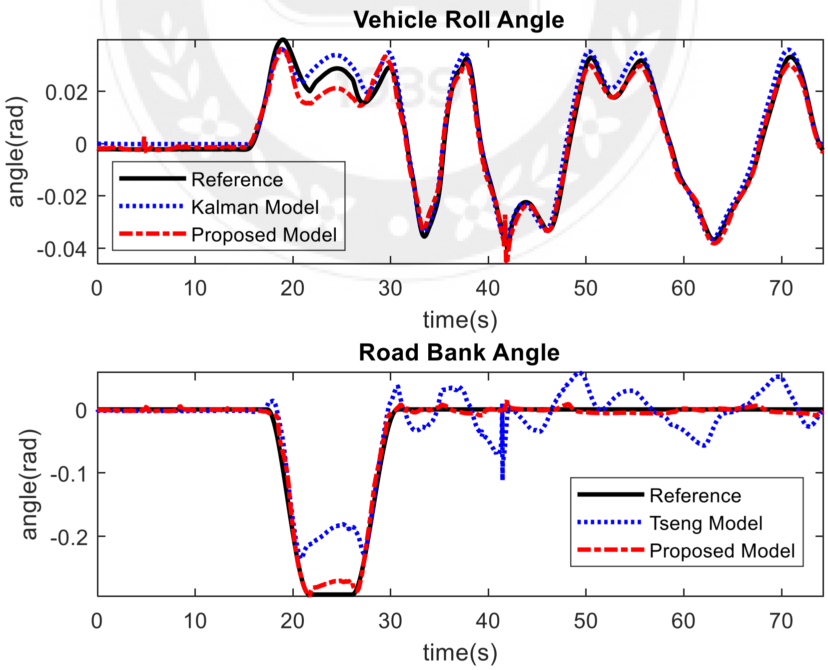

(a) Estimation result (70kph, 20% road bank angle)



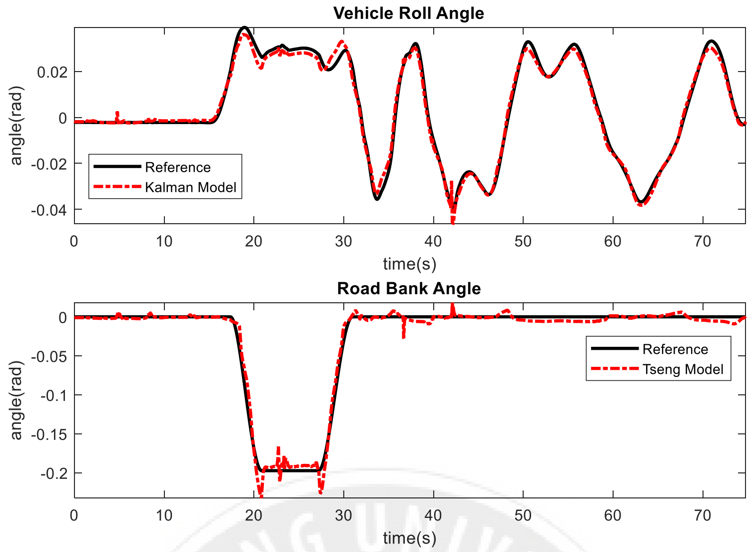

(b) Estimation result (70kph, 30% road bank angle)



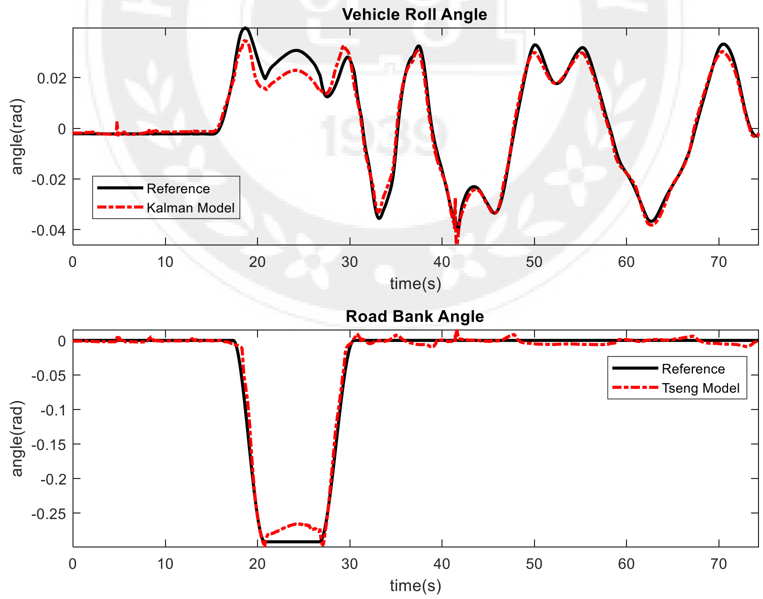

(c) Estimation result (100kph, 20% road bank angle)




(d) Estimation result (100kph, 30% road bank angle)




(c) Estimation result (130kph, 20% road bank angle)




(d) Estimation result (130kph, 30% road bank angle)

**Fig. 5-1 Simulation results**

# Chapter 5 Conclusion

In this paper, the vehicle roll angle and road bank angle estimation method using the DNN is proposed. To overcome weaknesses as neural networks go deeper, some techniques such as SELU, dropout etc. is used.

In order to validate the model, driving simulation on the test scenario was conducted. As a result, the proposed model shows robust characteristics for estimating two major parameters in high-speed driving scenarios. In the roll-angle estimation, the average root-mean-square error (RMSE) decreases by 18.6%. While, in the road bank angle estimation, the average RMSE decreases by 76.3%.

After this paper, the research can be further developed with more various driving situations as reverse-banked road, different friction coefficient(mu) road, driving with road disturbance etc. Moreover, not only one DNN model, but mode change with many DNN models depending on driving situation could be considered.

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# 국 문 요 지

이태희

미래자동차공학과

한양대학교

차량 주행 상황에서, 도로 뱅크 각은 차량 롤 운동 뿐만 아니라 차량 안정성에도 영향을 미친다. 보다 안정되고 안전한 주행 상태를 위해서는 차량 상태를 정확하고 안정적으로 추정하는 것이 중요하다. DFC 모델을 이용한 종래의 도로 뱅크 각 추정 방법은 정상 주행 조건에서는 좋은 추정 성능을 보이나, 고속 등의 불안정한 주행 상태에서는 추정 오차가 커진다.

본 연구는 심층신경망을 이용한 차량 롤 각 및 도로 뱅크 각 추정 방법을 제안하고자 한다. 차량 롤 각도와 도로 뱅크 각도를 추정하기 위해 널리 사용되는 차량 온보드 센서 중에서 다섯 개의 센서 데이터가 사용된다. 제안된 심층 신경망은 다양한 운전 상황에서 얻어진 입력 데이터를 이용하여 학습된다.

본 연구에서는 시뮬레이션을 통해 데이터 획득 과정 및 추정

알고리즘 검증을 수행 하였다. 차량 주행 시뮬레이션 및 차량 센서 데이터 수집은 차량 시뮬레이션 소프트웨어인 IPG Carmaker를 이용하였다. DNN 모델의 설계 및 훈련은 Python의 Keras를 사용했다.

시뮬레이션 결과는 DNN을 이용한 제안 된 방법의 성능이 기존의 방법보다 차량 롤 각과 도로변 각 추정에서 더 정확함을 보여준다. 특히 도로 뱅크 각도 추정에서 제안하는 방법은 더 나은 성능을 보인다.

# 연구 윤리 서약서

본인은 한양대학교 대학원생으로서 이 학위논문 작성 과정에서 다음과 같이 연구 윤리의 기본 원칙을 준수하였음을 서약합니다.

첫째, 지도교수의 지도를 받아 정직하고 엄정한 연구를 수행하여 학위논문을 작성한다.

둘째, 논문 작성시 위조, 변조, 표절 등 학문적 진실성을 훼손하는 어떤 연구 부정행위도 하지 않는다.

셋째, 논문 작성시 논문유사도 검증시스템 "카피킬러"등을 거쳐야 한다.

2018년12월17일

학위명 : 석사

학과 : 미래자동차공학과

지도교수 : 윤상원

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한 양 대 학 교 대 학 원 장 귀 하

# Declaration of Ethical Conduct in Research

I, as a graduate student of Hanyang University, hereby declare that I have abided by the following Code of Research Ethics while writing this dissertation thesis, during my degree program.

"First, I have strived to be honest in my conduct, to produce valid and reliable research conforming with the guidance of my thesis supervisor, and I affirm that my thesis contains honest, fair and reasonable conclusions based on my own careful research under the guidance of my thesis supervisor.

Second, I have not committed any acts that may discredit or damage the credibility of my research. These include, but are not limited to : falsification, distortion of research findings or plagiarism.

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