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A Fast and Reliable Approach for Driving Style Customization in Autonomous Vehicles

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***Abstract*— The usage of autonomous vehicles in the transportation sector can achieve the objective of a safe environment. To increase riding comfort in an autonomous vehicle, one main challenge is to implement motion scenarios according to the passenger's driving behaviours. This leads to customization of the driving style of an autonomous vehicle according to the preference of its passenger. The main disadvantage of the current autonomous vehicles is the regeneration of driving motion signals without taking into consideration the comfort/discomfort of the passengers according to their driving behaviours and preferred driving styles such as acceleration/deceleration rate and steering styles. In this paper, a nonlinear autoregressive network model is developed and trained based on the generated motion scenarios of the passenger and the position of the autonomous vehicle, in order to predict and replicate the motion signals based on the passenger's driving behaviours. The MATLAB toolbox is used to train the network and forecast the motion signals. The results show the usefulness of the proposed method in terms of a higher shape similarity level and a lower mean square error rate between the actual and forecasted motion signals. These regenerated motion signals can increase the riding comfort of autonomous vehicle's passengers as it is able to imitate the behaviour of the passengers.**

I. Introduction

An autonomous vehicle can be used in many applications, which include transportation, aerospace and military domains [1-3]. Indeed, autonomous vehicles will be part of human lifestyle in the near future. Autonomous vehicles can be designed based on a number of factors, such as high-quality maps, location recognition, obstacle perception, drivers and pedestrians interaction, as well as motion signal prediction [4, 5]. Jalali et al. [6] work on optimal autonomous driving technique using deep imitation learning and neuro evolution. In this respect, an accurate prediction of the motion signals is the core of the design process of autonomous vehicles because of its complexity and uncertainty. It plays the leading role in decision making and risk analysis of the operation of autonomous vehicles. Parallel and serial robots [7-10] are recently employed to study the driving motion sensation of newly designed vehicles, including the autonomous vehicles, in a safer and realistic environment such as a motion simulator platform [11-13].

Lefevre et al. [4] categorized the motion signal prediction of intelligent vehicles into three groups, viz., physics-based, manoeuvre-based, and interaction-aware. Mozaffari et al. [14] presented different categories of motion signals based on the input, output and prediction. Kiran et al. [15] surveyed motion signal prediction methods using reinforcement learning techniques in autonomous vehicles. Altche and de La Fortelle [16] used the long short-term memory (LSTM) model to predict the motion signal of autonomous vehicles in highways along with longitudinal and lateral channels. The method was able to increase the prediction accuracy and satisfy the requirements in state-of-the art applications. Xin et al. [17] increased the number of LSTM models, in order to indicate the intention of the driver and predict the motion signals with a long prediction horizon. Deo and Trivedi [18] improved the work of Xin et al. [17] to increase the accuracy using a multi-layer LSTM method. Zhao et al. [19] proposed the first combination between a conventional neural network (CNN) and the LSTM model to concatenate the driver action and road status. Lee et al. [20] proposed a fully-connected CNN model to forecast the lane change and control the operation using model predictive control. Later, Hu et al. [21]and Casas et al. [22] employed semantic-based intention and IntentNet to predict the motion signals with higher accuracy, respectively. Jalali et al. [23, 24] used neuro evolutionary technique for navigation of autonomous vehicle. Jalali et al. [25] used a CNN-LSTM deep learning method for prediction of solar irradiance. Also, Jalali et al. [26] proposed the neuro evolutionary CNN algorithm for intelligent load forecasting. Lately, Jalali et al. [27] used chaotic levy grasshopper optimization in new neuro evolutionary algorithm for short-term wind speed forecasting. Qazani et al. [28] used fuzzy type-2 neural network model for prediction of motion signal in short-time horizon with higher accuracy.

The main objective of this study is to customise the driving style of an autonomous vehicle according to the passenger's driving behaviour. Based on the best knowledge of the authors this has not been done yet. The consideration of the autonomous passengers' behaviours can increase the riding comfort instead of using machinery data. This will be conducted using a nonlinear autoregressive network to accurately predict the motion scenarios according to the passenger's driving style with a lower computational load. As compared with the existing complex methods [15-20], our

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proposed method aims to increase its applicability in real-time environments. However, they [15-20] focused on predictions rather than customisation of driving style. A lower computational load prediction method was introduced by Mohammadi et al. [29], in which a feedforward neural network (NN) model and the averages of historical and future motion signals history as the input and output of a prediction model were formulated. It should be noted this method has been implemented for the motion cueing algorithm (MCA) applications [30-34] in driving simulators [35-37] and has not been used in any autonomous vehicles. MCA is defined as a methodology to recalculate the real vehicle motion signal for the simulator with respecting the workspace limitations an regenerating same motion feeling for the user as same as real vehicle. Jalali et al. [38] developed a benchmark for training of multi-layer NN using metaheuristic algorithms.

Fig. 1 shows a schematic structure of the autonomous vehicle, along with its sensors and batteries. In this research, a nonlinear autoregressive network using the Levenberg-Marquardt (LM) training technique is employed to predict the motion signals of the autonomous vehicle based on the driving style of the passenger. The main disadvantage of the current intelligent vehicles is the regeneration of motion signals without taking into consideration the comfort/discomfort of the passengers according to their driving behaviours and preferred driving styles such as acceleration/deceleration rate and steering styles. It is worthwhile to use the motion signals from the driving style of the passenger in the NN training process to regenerate more human-like motion signals. It should be noted that the nonlinear autoregressive network is faster than LSTM, leading to its potential in online training during the motion of the autonomous vehicle. In addition, the nonlinear autoregressive network has more inputs in contrast with the feedforward NN model, allowing it to achieve a higher accuracy rate with a highly nonlinear model [39, 40].

This paper is organized as follows. The methodology of the existing feedforward NN model and the recently developed nonlinear autoregressive network are described in Section II. The usefulness of the proposed method is investigated in Section III. The results indicate the high efficiency of the proposed method as compared with those of the existing methods. In Section IV, conclusions of this study are presented.

II. Methodology

Two methods are investigated in this study to predict the motion signals, including a feedforward NN model and a nonlinear autoregressive network due to their faster training process and potential in online training during the autonomous vehicle riding. They are the fastest methods in terms of training time, among other models.

A. Feedforward NN

Mohammadi et al. [29] proposed the feedforward NN model to predict the motion signals of a vehicle, in order to increase the efficiency of the motion simulator platform. Motion simulator platform can be parallel- or serial-based manipulators [41]. The lower computational load of their proposed method is the main advantage, which can be used in online training mechanism such as autonomous vehicles. The

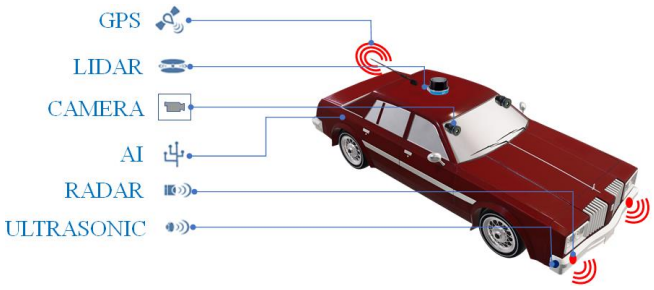


Fig. 1. The structure of the autonomous vehicle with sensors.

input of the feedforward NN is a combination of the past motion signals, which aims to enhance the prediction accuracy pertaining to the motion signals. On the other hand, the average of the past motion signals is used to decrease the computational time during the training process of the network. The input and output data are divided into ten and one groups, respectively, as:

$$\mathbf{U}_{\text{in}}(i) = \left[\bar{u}_{in,1}, \cdots, \bar{u}_{\text{in},m}(i), \cdots, \bar{u}_{in,5}\right] \quad (1.a)$$

$$\mathbf{U}_{\text{out}}(i) = u_{out,1} \quad (1.b)$$

where $\mathbf{U}_{\text{in}}$ and $\mathbf{U}_{\text{out}}$ are the input and output vectors of the model at the i^{th} time. Note that $\bar{u}$ is the average of each group of the past motion signals, which can be calculated as follows:

$$\bar{u}_{\text{in},m}(i) = \frac{1}{n_{\text{in},m}} \sum U_{\text{in},m}(i), \qquad m = 1,2,\dots,5 \quad (2)$$

where U_{in} is the past motion signals divided into ten groups. The entire sample time of each group is different. The group closer to the current time has a higher resolution using fewer motion signals, as compared with those of more extended groups. A single-layer feedforward NN model with 50 neurons is used in this study to achieve the trade-off of a reasonable accuracy rate and a lower computational load during the network training process.

B. Nonlinear Autoregressive Model

The nonlinear autoregressive network was introduced by Chow and Leung [42] to deal with time-series data. A nonlinear autoregressive network is based on the modification of a feedforward NN model, which has been used in many areas such as energy and geographical applications [43, 44]. Fig. 2 shows a schematic representation of a nonlinear autoregressive network with a combination of the external variables using two and three time-step delays along with the output and external variable, respectively. It contains three layers, namely, the input, middle and output layers. In this study, the exogenous inputs are employed as the position of the vehicle in the road map, in order to increase accuracy of the method. The output is calculated as follows:

$$y(t) = f\left(y_{t-1}, \cdots, y_{t-n_y}, u_{t-1}, \cdots, u_{t-n_u}\right) + \epsilon_t \quad (3)$$

where y, u and ϵ are the output, external variable and noise of the model, while n_y and n_u are the delay of the output and external variable, respectively. In addition, f is a nonlinear function used to predict the output based on past signals and external variable. The LM method is used to train the network as it is the fastest algorithm to produce reasonable results. The Hessian matrix is calculated based on the Jacobian matrix, i.e.,

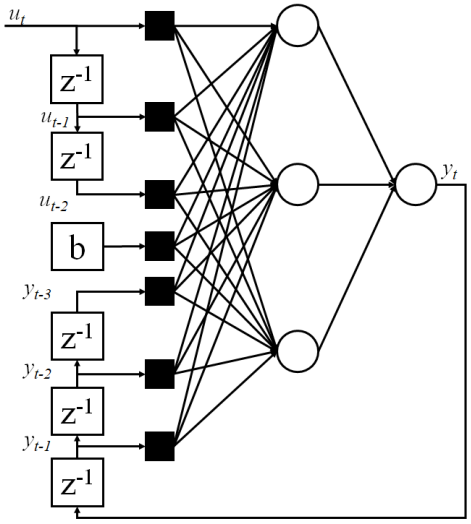


Fig. 2. The schematic representation of the nonlinear autoregressive network with combination of external variable.

$$\mathbf{H} = \mathbf{J}^{\mathrm{T}}\mathbf{J} \tag{4}$$

where **H** and **J** are the Hessian and Jacobian matrices. The Jacobian matrix is computed as follows:

$$\mathbf{g} = \mathbf{J}^{\mathrm{T}}\mathbf{e} \tag{5}$$

where **e** is the error of the model in each sampling time. To decrease the computation load of the training process, the backpropagation algorithm is used to define the Jacobian matrix, as follows:

$$x_{k+1} = x_k - (\mathbf{J}^{\mathrm{T}}\mathbf{J} + \mu\mathbf{I})^{-1}\mathbf{J}^{\mathrm{T}}\mathbf{e} \tag{8}$$

where μ refers to the learning rate of the network. The adjustment parameters of the LM method are chosen based on the work by Moré [45], in order to reach a high performance of the model.

III. Results and Discussion

Fig. 3a-b presents the graphical interpreter of the Rigs of Rod (RoR) soft body engine version 0.39.5 and a road map during the regeneration of motion signals as an input of the investigated data in Section II. The vehicle ride goes for 30 laps, in which 28 laps are used for training, one lap for validation and one lap for test. The motion signals to be predicted using the investigated methods are the linear acceleration signal and angular velocity along the three directions as well as the absolute velocity of the autonomous vehicle during the regeneration of motion scenarios.

Fig. 4a-b shows the training, validation and test error histograms from the feedforward NN and nonlinear autoregressive network with external variable, respectively. It contains twenty bins (shown as bars). The bins with the error of 0.4545 and 0.01625 contain the most sampling data of the feedforward NN and nonlinear autoregressive network with the existence of external variable, respectively. The error is the difference between the target and estimated data. As can be observed, the error histogram of the nonlinear autoregressive network with the existence of an external variable is symmetric, while it is highly skewed to the right side for the feedforward NN model. Finally, the higher accuracy of the

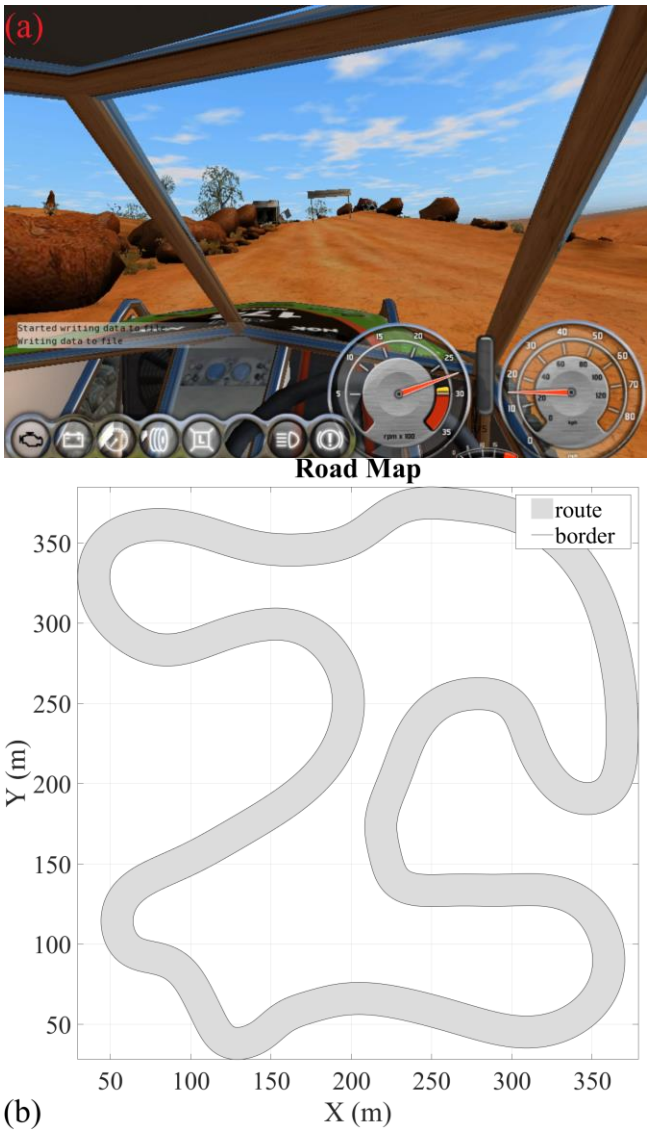


Fig. 3. (a) The graphical interpreter of the RoR software; (b): The used map for regeneration of the motion signals.

nonlinear autoregressive network with the external variable in contrast with the feedforward NN model is obvious, as shown in Fig. 4b.

Fig. 5a-b present the regression of the training, validation, and test phases of the feedforward NN model and nonlinear autoregressive network using the external variable, respectively. The horizontal and vertical axes in Fig. 5 indicate the target and predicted data of each model. The output of the feedforward NN model and the nonlinear autoregressive network are 6.1×10^{-6} and 4.1×10^{-8}, as in Fig.5a-b, respectively. The feedforward NN model cannot reach the ideal regression limit, which is equal to one, as shown in Fig. 5a. The nonlinear autoregressive network with the external variable can achieve the ideal regression limit, as shown in Fig. 5b.

Fig. 6a-b illustrate the performance of the feedforward NN and the nonlinear autoregressive network during the training, validation and test periods. The mean square error of the nonlinear autoregressive network is smaller than that of the feedforward NN model. The best validation results occur in epoch 129 and 131 with 6.5002×10^{-5} and 5.0495×10^{-6} yielded

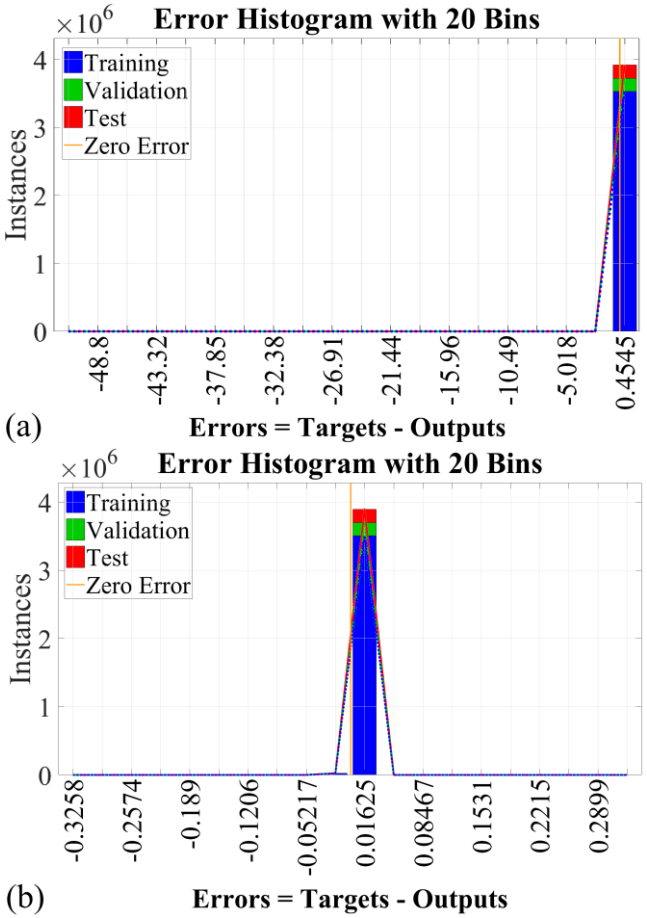


Fig. 4. The training, validation, and testing error histogram for estimation of the driving motion signals while using (a): feedforward NN; (b): nonlinear autoregressive with presentation of external variables.

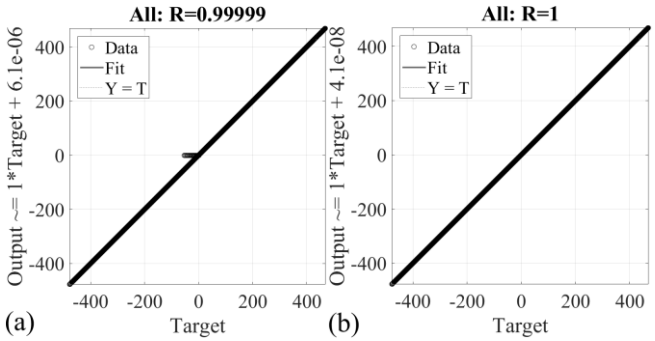


Fig. 5. The regression of the network during training, validation, and testing process using (a): feedforward NN; (b): nonlinear autoregressive with presentation of external variables.

by the feedforward NN model and the nonlinear autoregressive network, respectively.

The proposed networks are used to predict the motion indexes of the autonomous vehicle, including the linear acceleration and angular velocity along with three directions as well as the absolute speed of the vehicle. Fig. 7a-c show the error profiles between the real and forecasted motion signals, including the linear acceleration signal along the *x*-axis, angular velocity of the roll-angle, and absolute speed of the vehicle, respectively. Based on the presented results, the error rates between the real and forecasted motion signals reduces when the nonlinear autoregressive network is used, as

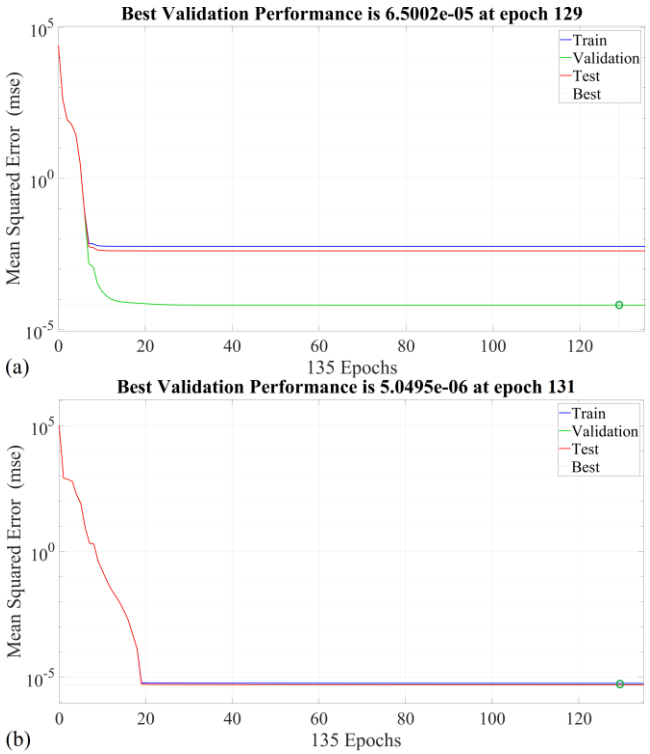


Fig. 6. The performance of the network during training, validation, and testing process and the best candidate using (a): feedforward NN; (b): nonlinear autoregressive with presentation of external variables.

compared with that of the feedforward NN model. Based on Fig. 7a, the maximum motion prediction error for te linear acceleration signal along the *x*-axis using the nonlinear autoregressive network reduces from 0.0909 to 0.0027 m/s^2 , in contrast with the feedforward NN model. The maximum motion prediction error for the angular velocity signal pertaining to the *roll*-angle using the nonlinear autoregressive network reduces from 0.0049 to 0.0035 rad/s in contrast with the feedforward NN model, based on Fig. 7b. Moreover, the maximum motion prediction error for the absolute speed of the autonomous vehicle using the nonlinear autoregressive network reduces from 0.0103 to 0.0028 m/s, in contrast with the feedforward NN model, based on Fig. 7c. Table I represents the root means square error (RMSE) between the real and forecasted motion indexes of the autonomous vehicle along three directions using both investigated methods. As indicated in Table I, the nonlinear autoregressive network outperforms the feedforward NN model in terms of accuracy (i.e. smaller RMSE score). The computational times of both methods in the training process on a computer with Intel(R)

TABLE I
THE ROOT MEANS SQUARE ERROR OF MOTION INDEXES USING FEEDFORWARD NN AND NONLINEAR AUTOREGRESSIVE NETWORK WITH EXISTENCE OF EXTERNAL VARIABLE

Index	Feedforward NN	Nonlinear Autoregressive
a_x	0.0018 m/s^2	1.6953×10^{-4} m/s^2
a_y	3.6495×10^{-4} m/s^2	3.4129×10^{-4} m/s^2
a_z	5.1952×10^{-4} m/s^2	1.7752×10^{-4} m/s^2
roll_dot	0.0327 rad/s	2.2634×10^{-4} rad/s
pitch_dot	0.0673 rad/s	3.0901×10^{-4} rad/s
yaw_dot	0.9991 rad/s	0.0072 rad/s
Absolut speed	4.3198×10^{-4} m/s	1.9930×10^{-4} m/s

m: meter; rad: radium; s: second.

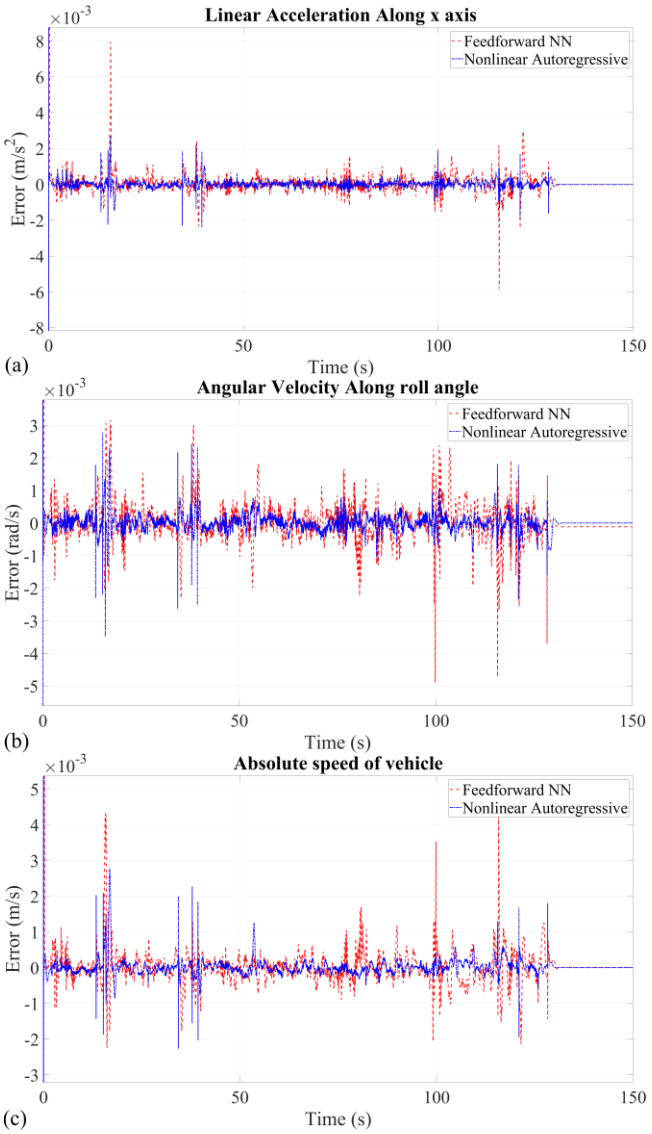


Fig. 7. The actual and predicted motion signal for the absolute velocity of the autonomous vehicle during the implementation of testing data from 30 to 50 seconds using (a): feedforward NN; (b): nonlinear autoregressive with presentation of external variables.

Core(TM) i7-9700K CPU @ 3.60GHz 3.60 GHz specification are compared. The feedforward NN model is trained in 94 minutes and 34 seconds, while the nonlinear autoregressive network is trained in 105 minutes and 21 seconds. It shows that the nonlinear autoregressive network with an external variable has an approximately low computational load as same as feedforward NN, while it can reach better results compared to the previous method.

In order to evaluate the repeatability of the proposed technique as compared with those of the previous technique, the experiment has been applied ten-times using both investigated methods. The results for the estimation of the linear acceleration signal along *x*-axis using feedforward NN and nonlinear autoregressive network has been shown in Fig. 8a-b for ten-times trials respectively. It shows that the error of the recently developed technique is less than previous technique. Also, it reveals that the distribution of the error using nonlinear autoregressive network is normal, while the error of the feedforward NN is screw right.

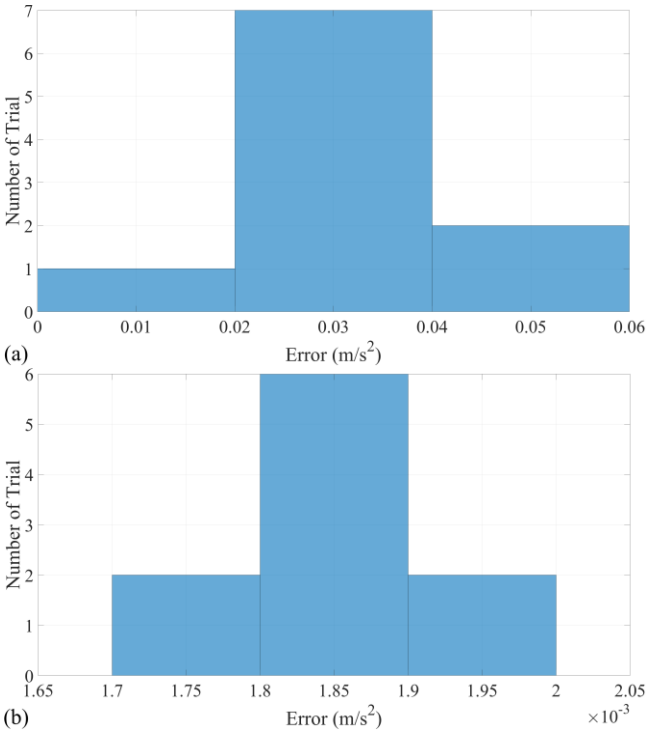


Fig. 8. The error histogram for ten-times trials of predicting linear acceleration signal along *x*-axis during the test using (a): feedforward NN; (b): nonlinear autoregressive network with external states.

Finally, it should be noted that the proposed method is able to predict the driving style of the autonomous vehicle's passengers to increase the riding comfort as a new generation of the intelligent vehicles. It is fast, and it is able to reach the reasonable accuracy with lower RMSE.

IV. Conclusion

Autonomous vehicles form an integral part of our future life. Currently, a passenger's driving style is not taken into consideration for regeneration of the motion signals in an autonomous vehicle, leading to possibly an unpleasant riding experience. Taking into consideration the passengers' driving behaviours and preferred driving styles such as acceleration/deceleration rate and steering styles is a very important factor as it plays the main role in autonomous vehicle riding comfort and acceptability. The feedforward NN and LSTM models have been used to predict the motion signals of autonomous vehicles, but they suffer from several limitations. Initially, they did not use to predict the style of the vehicle's passengers. Then, they regenerate machinery motion signal with less comfort. Moreover, the Feedforward NN is fast, it is not accurate. On the other hand, the LSTM model has a high computational load during the training process. In this study, a nonlinear autoregressive network with external presence is used to predict the motion signals of an autonomous vehicle, in order to imitate the driving behaviours of the passenger of an autonomous vehicle, satisfy accuracy and low computational requirements of the training process. Both feedforward NN and nonlinear autoregressive network are designed and developed using the MATLAB software. The motion indexes of a vehicle are recorded using

the soft body engine software (RoR), including linear and angular motion of the vehicle. The results prove the higher efficiency of the proposed nonlinear autoregressive network, as compared with those of a feedforward NN model. The proposed method yields a low error rate between the real and forecasted motion signals without a high computational load and long training process, leading to its possible real-time implementation in future autonomous vehicles. As a future work, the driver sensation in autonomous vehicle can be objectively and subjectively measured using mathematical model of human vestibular system [46-51] . Also, the idea of machine learning [52], model predictive control [53-56] and meta-heuristic algorithm [57-59] can be used to assess human factors [49] aiming to validate the MCA performance. Also, the fuzzy can be applied in autonomous vehicle as it has been widely applied in different domains [60-64].

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