PriMera Scientific Engineering
Volume 6 Issue 1 January 2025
ISSN: 2834-2550

Machine Learning Based Torque Monitoring Algorithm for Preventing Unintended Acceleration and Deceleration in Vehicles

Type: Review Article
Received: October 23, 2024
Published: December 19, 2024

Citation:
Byunggun Kim., et al. "Machine Learning Based Torque Monitoring Algorithm for Preventing Unintended Acceleration and Deceleration in Vehicles". PriMera Scientific Engineering 6.1 (2025): 51-59.

Byunggun Kim*, Eunsang Park, Doin Kwon, and Hyunki Shin

Control Solution Center, Hyundai Kefico, 102 Gosan-ro, Gunpo, Gyeonggi-do, Korea

***Corresponding Author:** Byunggun Kim, Control Solution Center, Hyundai Kefico, 102 Gosan-ro, Gunpo, Gyeonggi-do, Korea.

Abstract

The primary purpose of E-GAS monitoring is to ensure the functional stability of the electronic controller in relation to vehicle torque. At level 2 of the E-GAS monitoring concept, the calculation of permissible torque typically relies on formula-based models that simplify real vehicle behavior, accompanied by complex calibration to enhance accuracy. However, this approach often fails to adequately account for the diverse driving scenarios encountered by the vehicle. To address this limitation, this study proposes an algorithm for calculating permissible torque using machine learning at level 2 of the E-GAS monitoring concept. The effectiveness of the algorithm is validated through the analysis of real-world vehicle driving data, confirming its practicality and applicability.

Keywords: E-GAS Monitoring Concept; Torque Monitoring; Machine Learning; Electric Vehicle; Functional Safety; Vehicle Control Unit (VCU)

Introduction

There is a growing global awareness of energy conservation and environmental protection. As a result, governments worldwide are increasingly strengthening regulations on fuel efficiency and exhaust emissions, and the prospects for electric vehicles are expanding. As the adoption of electric and eco-friendly vehicles accelerates and vehicle performance advances, various electronic control units are being installed in vehicles to ensure proper control. However, the increased complexity of electrical components and systems also introduces a higher likelihood of errors occurring in electronic control systems. Ensuring the functional safety of electronic control units has become increasingly important, particularly in the context of vehicle torque control. Errors in torque control can lead to unintended fluctuations in torque, potentially resulting in severe accidents. Therefore, ensuring high levels of functional safety in torque control systems is crucial for vehicle safety.

To ensure the functional safety of torque-related electronic control units in vehicles, the concept of E-GAS monitoring is widely applied. This concept, developed by European automotive original equipment manufacturers (OEMs), aims to prevent accidents caused by errors in electric and electronic (E/E) systems installed in diesel/gasoline vehicles [1]. The E-GAS monitoring concept consists of three levels and employs a hierarchical structure with redundancy to ensure functional safety. Although initially designed for vehicles equipped with engine control systems, such as diesel/gasoline vehicles, the E-GAS monitoring concept has also been considered and utilized in torque monitoring systems in electric vehicles due to the increasing popularity of environmentally friendly electric vehicles with enhanced performance [2, 3]. However, determining the permissible torque for monitoring requires simplified modeling of the actual vehicle behavior and complex calibration tasks.

Meanwhile, machine learning, which has gained significant attention in the era of the Fourth Industrial Revolution, is widely utilized in various fields for fault detection and anomaly identification in mechanisms. Long Short-Term Memory (LSTM) network models, suitable for handling time-series data, have been have been successfully used in various applications such as detecting engine clutch anomalies in P2 hybrid electric vehicles (HEVs), diagnosing faults in rotating systems, and detecting anomalies in drone motors [4-6]. Machine learning provides meaningful research outcomes in solving problems that typically require extensive manual adjustments and rules, fault detection and diagnosis in dynamic environments, and complex issues that are challenging to address using traditional approaches.

This paper aims to ensure the functional safety of the Vehicle Control Unit (VCU), a key electronic control unit in electric vehicles, in line with the functional safety objectives. To achieve this, we propose a torque monitoring algorithm based on the E-GAS monitoring concept to prevent unintended accelerations and decelerations in vehicles. We leverage machine learning, specifically the LSTM network model that addresses the gradient vanishing problem in Recur rent Neural Network (RNN) models and excels in processing time-series data. The machine learning models are trained and validated using processed real world driving data from an HYUNDAI IONIQ 5 electric vehicle.

Concept of E-G AS Monitoring

The concept of E-GAS monitoring was developed by European automotive Original Equipment Manufacturers (OEMs) to ensure the functional safety of both diesel and gasoline vehicles. The core of the E-GAS monitoring concept is a three level architecture that monitors the engine control system and prevents potential risks caused by unexpected errors (refer to Fig. 1).

The first level is the Function level, which includes basic engine control functions such as requested engine torque conversion, component monitoring, and input/output variable diagnostics. It also includes diagnostic and error handling functions. The second level is the Function monitoring level, which monitors the calculated torque value or vehicle acceleration to detect any faults in the basic functions of the first level. The third level is the Controller monitoring level, which includes independent modules for monitoring and verifies the correct operation of functions through a question-answer process. In other words, the E-GAS monitoring concept ensures redundancy through the hierarchical structure of the three levels. By placing backup devices, the system can continue to operate even in the event of unexpected errors in certain parts of the system. This enables the detection of abnormal vehicle conditions, the handling of system errors that may endanger the safety of vehicle occupants, and the assurance of functional safety. Typically, the calculation of allowable torque for the second level torque monitoring, in accordance with the E-GAS monitoring concept, requires formula-based modeling that simplifies the vehicle's behavior and complex calibration. This involves significant effort and resources. Moreover, such modeling is challenging to adapt to changes in various vehicle factors due to changes in vehicle durability. Consequently, the vehicle modeling used in the conventional calculation of allowable torque for torque monitoring is inadequate in adequately reflecting the various driving situations of the vehicle. To address this, this study proposes an algorithm that calculates the allowable torque in accordance with the E-GAS monitoring concept using actual vehicle driving data and machine learning.

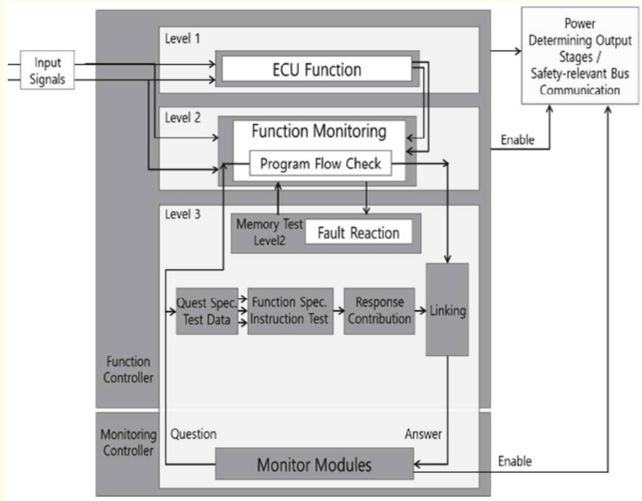


Figure 1: E-GAS Monitoring Architecture Concept.

Machine Learning

Based on the E-GAS monitoring concept mentioned in Sect. 2, the machine learning network model used in this paper to determine the second level allow able torque is represented by the following Eq. (1). The input data accumulates past values.

$$T_{\mathrm{per}}(t) = g\left((f_{1,t-h-1}, f_{2,t-h-1}, \ldots), \ldots, (f_{1,t-h}, f_{2,t-h}, \ldots), (f_{1,t}, f_{2,t}, \ldots)\right) \times W \quad (1)$$

In Eq. (1), T_{per} represents the permissible torque, *t* represents the target timestamp, *g* represents the network model that takes time series data as input, *h* represents the stack size for accumulating data, *f* represents the features of the data used for machine learning, and *W* represents the weights for setting the allowable torque.

Dataset Creation

Creating a high-quality dataset is essential for improving the performance of machine learning. To create the dataset, real-world driving data was obtained using HYUNDAI IONIQ 5 electric vehicle. In this paper, six factors were selected as predictors for predicting the drive torque for allowable torque calculation: vehicle speed, Road slope, Accelerator Position Sensor (APS), Brake Position Sensor (BPS), BPS on/off signal, and gear position (P, N, D, R). The acceleration component can have a negative impact on prediction performance due to small values and variations caused by noise. To address this, the past values of speed were accumulated and used in the network training to enable the network to infer the acceleration component. In addition, in the case of road slope, it is measured in real time using an Extended Kalman Filter (EKF). The selected factors and the corresponding drive torque timestamps were synchronized through interpolation to create the datasets. If the selected factors have different scales, it can negatively affect the learning process. To prevent this, normalization was applied to ensure that the data characteristics of each factor are represented on a similar scale. The processed datasets were divided into a randomly selected test set (TestX, TestY) and a training set (TrainX, TrainY) to be used for training the network and evaluating its performance.

LSTM Network Architecture

RNN (Recurrent Neural Network) is renowned for its ability to reflect past information into the current learning process, making it suitable for sequence data and time series data. However, traditional RNNs suffer from the issue of vanishing gradients during the backpropagation process, which significantly impairs the network's learning capacity. To address this issue, the LSTM (Long Short-Term Memory) model was introduced.

LSTM enhances the standard RNN architecture by introducing a cell state in addition to the hidden state. In this study, LSTM is employed for drive torque prediction. The cell structure of LSTM is depicted in Fig. 2.

The cell state plays a role in maintaining the information flow without significant changes. The forget gate determines which information to discard based on past information, while the input gate determines how to store and incorporate new information. The cell state update is performed by considering the information to be discarded and the information to be stored from the forget gate and input gate. The output gate determines how the information from the cell state should be emitted. Multiple cells are combined to form a complete LSTM. The flow of the LSTM can be described by the following equations.

$$f_t = \sigma(w_f \cdot [h_{t-1}, x_t] + b_f) \tag{2}$$

$$i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i) \tag{3}$$

$$o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o) \tag{4}$$

$$g_t = \tanh(w_g \cdot [h_{t-1}, x_t] + b_g) \tag{5}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot g_t \tag{6}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{7}$$

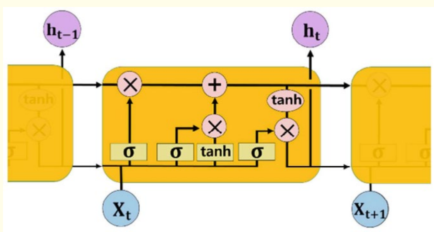


Figure 2: Cell Structure of LSTM.

The proposed network in this study performs the drive torque prediction at the target timestamp by considering the past factors based on the value of Stack size, which represents the amount of accumulated data. A larger Stack size incorporates a longer duration of past data to predict the drive torque at the target timestamp, while a smaller Stack size reflects a shorter duration of past data. In this study, an appropriate Stack size of 10 was chosen to allow the network to capture the vehicle's dynamic characteristics effectively. With a data synchronization interval of lOOms, a Stack size of 10 predicts the drive torque at the target timestamp based on the features of the past 1 s of data. (refer to Fig. 3).

The network was constructed using PyTorch, and its architecture is illustrated in Fig. 4.

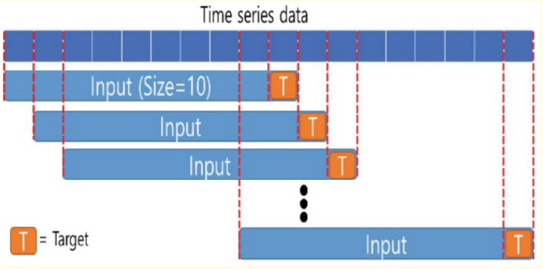


Figure 3: Block Diagram of Input and Output with Stack size of 10.

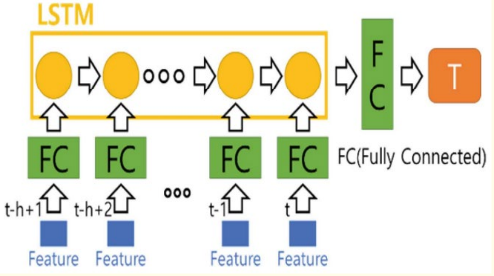


Figure 4: Proposed Network Architecture.

Network Performance Evaluation

The network's performance evaluation is conducted using a test set that was not used for training from the created dataset. The predicted drive torque results based on the driving time are depicted in Fig. 5. It can be observed that the network demonstrates effective drive torque prediction performance even in challenging situations such as acceleration and deceleration, where prediction is relatively difficult compared to normal driving. The total measurement time for the entire driving data is approximately 185 minu (about 11,100 seconds), with approximately 35 minu (about 2,100 seconds) used as the test data.

Generally, accurate prediction of a vehicle's drive torque requires precise estimation of various factors included in the vehicle model, considering non-linear characteristics such as rolling resistance, air resistance, and slope resistance. However, the approach proposed in this study utilizes real-world driving data, allowing the machine learning network model to incorporate the non-linear and durability-induced variations of factors, yielding relatively valid results. By calculating the permissible torque of the vehicle using this method, more effective results that better reflect the characteristics of actual vehicle driving can be obtained.

In this study, the machine learning network predicts the normal torque value even when unexpected torque occurs due to vehicle issues. Through this, the permissible torque is calculated to ensure system redundancy and maintain the functionality of the vehicle system.

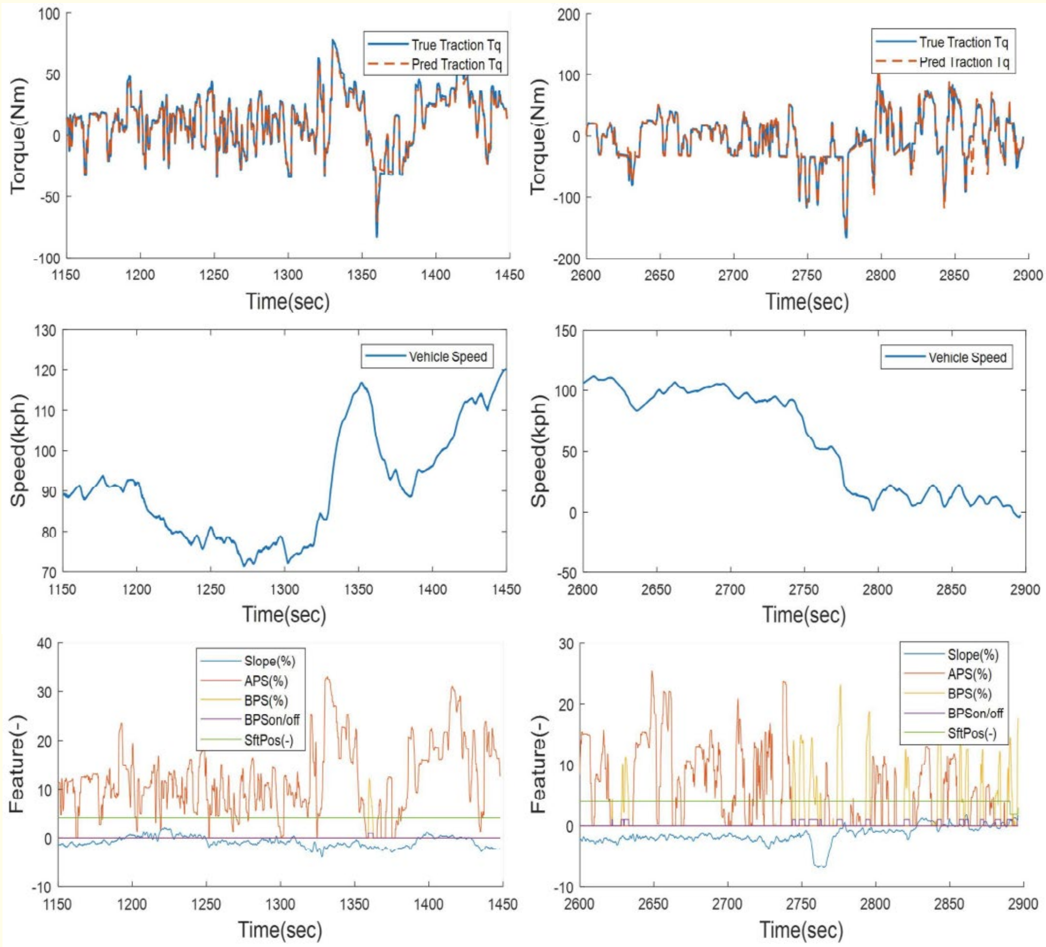


Figure 5: Evaluation of Drive Torque Prediction Performance.

Machine Learning-Based Torque Monitoring Algorithm

Overview of the Proposed Algorithm

The algorithm proposed in this study can be represented as shown in Fig. 6. Based on the predicted drive torque values obtained from machine learning in Sects. 2 and 3, the level 2 permissible torque is calculated by multiplying them with the weight W. To minimize unnecessary detection in the low torque range, an offset is applied. Additionally, a marker called the Check Point (CP) is introduced to detect faults during the debouncing period. CP is generated when the actual torque value of the vehicle deviates from the permissible torque range calculated using the proposed algorithm. The CP value is set to 1 if it deviates within the positive torque range and -1 if it deviates within the negative torque range. If the number of CPs generated exceeds 5 within 1 second, it is considered a fault detection in the vehicle, and appropriate failure measurement actions are taken based on the algorithm.

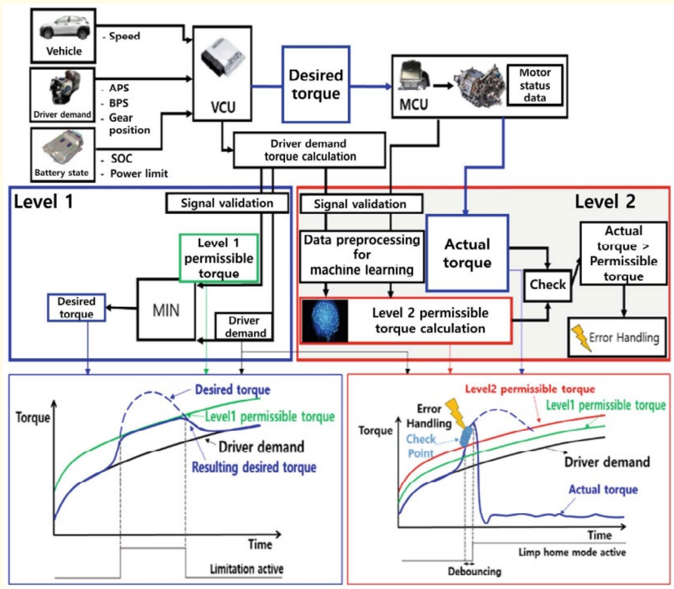
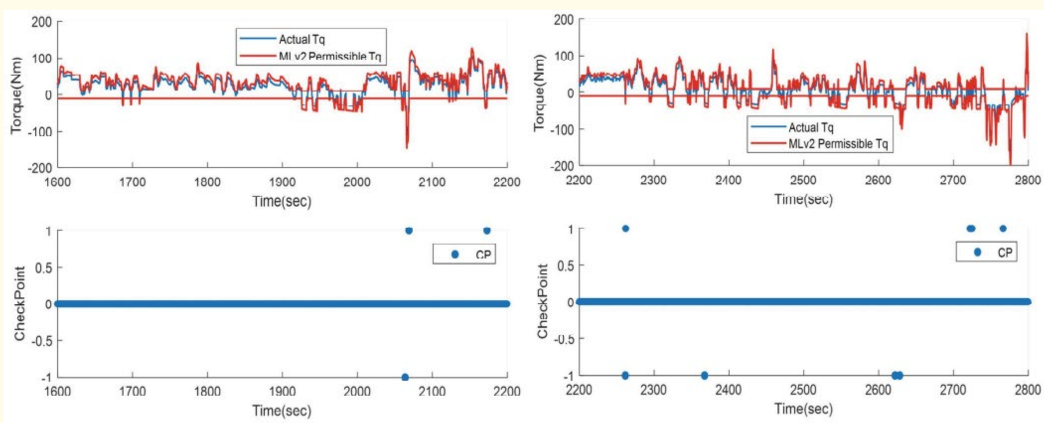


Figure 6: Overview of the Proposed Algorithm.

Performance Verification of the Proposed Algorithm

The performance verification results of the proposed algorithm are shown in Fig. 7. The MLv2 Permissible Torque (Machine Learning Lv2 Permissible Torque) is calculated by multiplying the predicted drive torque values with a weight of W=l.25. It has been verified that this calculation is suitable for performing the level 2 torque monitoring function in accordance with the E-GAS monitoring concept. In cases where the vehicle's movement is abrupt, Check Points (CPs) are generated within a short period of time, but they do not exceed the specified threshold, indicating no fault detection. The effectiveness of the proposed algorithm is evaluated, considering acceleration, deceleration, and the duration of stationary intervals until the vehicle comes to a complete stop.



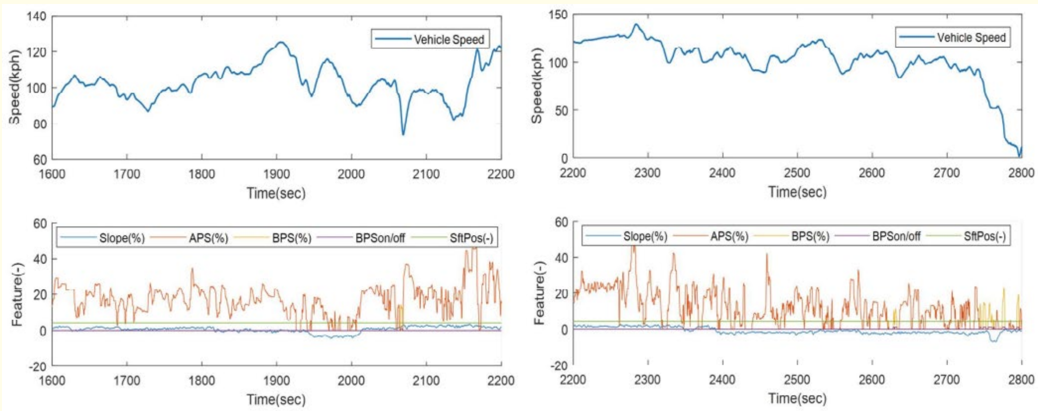


Figure 7: Verification of the Machine Learning-Based Torque Monitoring Algorithm.

Conclusion

In this study, machine learning was utilized in the level 2 torque monitoring algorithm, which aligns with the E-GAS monitoring concept, to detect unintended acceleration and deceleration of vehicles. Typically, calculating the permissible torque for the level 2 torque monitoring, which complies with the E-GAS monitoring concept, requires inaccurate formula-based vehicle modeling and complex calibration tasks for compensation. Such modeling is based on calibrated data from the pre-development stage of the vehicle, making it difficult to reflect the variations in vehicle factors due to changes in vehicle durability. Consequently, considering a wide range of driving conditions in torque monitoring based on the conventional methods becomes challenging. Therefore, in this study, a permissible torque calculation algorithm was proposed and validated, utilizing real-world driving data and machine learning that aligns with the E-GAS monitoring concept. Future research plans to focus on implementing fault mitigation measures to safely stop the vehicle when faults are detected using the proposed algorithm. Simulation tools will be used to create scenarios for verification and assess the effectiveness of this research. Additionally, further enhancements will be made to the machine learning network by selecting additional factors to improve the performance of drive torque prediction and calculate more effective permissible torque. Particularly, the current machine learning network does not utilize information about the battery, but regenerative braking can affect the drive torque, and the amount of regenerative braking is related to the state of the battery. Therefore, future research will consider the incorporation of battery related information in the analysis.

Acknowledgments

This work was supported by the Hyundai Motor Group (HMG, Korea).

References

1. Standardized e-gas monitoring concept for gasoline and diesel engine control units version 6.0. Technical report (2020).
2. Yi F, Zhang W and Zhou W. “Functional safety design for torque control of a pure electric vehicle”. In: 2021 9th International Symposium on Next Generation Electronics (ISNE), IEEE (2021): 1-4.
3. Xin Z., et a. “Research of driving torque monitoring for electric vehicle”. In: 2021 IEEE International Conference on Emergency Science and Information Technology (ICESIT), IEEE (2021): 31-34.
4. Ji Y and Lee H. “The LSTM-based engine clutch engagement/disengagement anomaly detection algorithm for p2 HEV”. Trans. Korean Soc. Autom. Eng 29.12 (2021): 1133-1146.

5. Lee D., et a. "Anomaly detection in rotating motor using two-level LSTM". In: Proceedings of KIIT Conference (2021): 425-428.
6. Lee Y-K, Hong S-C and Hong J-K. "LSTM-based drone's anomal motor vibration detection system". J. Inf. Technol. Archit 17.4 (2020): 315-321.