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A Deep Learning-Based Anomaly Forecasting System of Time Series Sensor Data in Autonomous Vehicles*

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Abstract— **This study investigates the application of a hybrid ARIMA–Transformer time series forecasting model—previously validated in smart factory environments—to autonomous vehicle sensor data, in order to evaluate its domain scalability and practical feasibility. The hybrid architecture, which combines the linear forecasting capability of ARIMA with the nonlinear temporal modeling strength of the Transformer, demonstrated robust and reliable performance under complex and uncertain autonomous driving scenarios. Experimental evaluations using real-world sensor data confirmed the model's superior accuracy under both normal and anomalous conditions. These findings underscore the potential of hybrid forecasting approaches in transportation and mobility systems, contributing to improved reliability in autonomous driving technologies.**

I. INTRODUCTION

Autonomous vehicles rely on a variety of sensors such as LiDAR, RADAR, ultrasonic sensors, and cameras to perceive their surrounding environments and internal states in real time. The accuracy and continuity of these sensor signals are critical for ensuring driving safety and maintaining vehicle performance. However, sensor data are often subject to anomalies caused by noise, hardware malfunctions, or communication delays, which may lead to erroneous decisions or even accidents. Therefore, the early detection and forecasting of such anomalies are essential to enable safe and reliable autonomous driving.

Traditional statistical methods face limitations in modeling the complex, nonlinear patterns commonly found in sensor data. In contrast, deep learning approaches—such as Long Short-Term Memory (LSTM) networks and Transformers—have demonstrated strong capabilities in capturing long-range temporal dependencies and diverse time series dynamics. In particular, unsupervised methods that combine self-supervised learning [1] with Variational Autoencoders (VAEs) [2] have achieved promising results, especially in real-world autonomous driving scenarios where labeled data are scarce. These techniques are increasingly becoming core components of intelligent sensor data analysis systems.

Recently, LSTM- and Transformer-based models have gained increasing attention for anomaly forecasting in autonomous vehicle sensor data. While LSTM models effectively capture sequential temporal dependencies, Transformer architectures employ attention mechanisms to model complex inter-variable relationships in parallel. Furthermore, hybrid approaches that integrate ARIMA with Transformer architectures have been proposed to enhance forecasting performance by capturing both linear and nonlinear components of time series data.

In this paper, we adopt a hybrid ARIMA–Transformer model previously validated in the smart factory domain [3], [4] for autonomous vehicle sensor forecasting. We design a high-reliability forecasting system tailored to the complexity and uncertainty of autonomous driving environments. Using real-world sensor datasets, we quantitatively evaluate the performance of the proposed method under both normal and anomalous conditions. This study expands the application of hybrid forecasting techniques to the domain of intelligent mobility, offering valuable insights for time series analysis in autonomous driving systems.

The remainder of this paper is organized as follows. Section II introduces the key sensors used in autonomous vehicles. Section III describes Hybrid I and Hybrid II, the core models of the proposed forecasting system. Section IV presents the datasets, experimental settings, and forecasting results. Finally, Section V concludes the paper with a summary of the key findings.

II. SENSOR DATA OF AUTONOMOUS VEHICLES

Autonomous vehicles deploy a variety of sensors distributed around the front, rear, and sides of the vehicle to perceive and interpret complex road environments in real time. Fig. 1 illustrates an example of the placement and roles of these sensors. Each sensor collects surrounding information in a unique manner, which is then converted into time series sensor data used for driving decisions, path planning, and control. The main sensors include cameras, RADAR, LiDAR, ultrasonic sensors, and firmware modules.

Cameras are mounted on the front and sides of autonomous vehicles to provide visual perception of road lanes, traffic signs, vehicles, and pedestrians. While the raw image frames are not time series data in themselves, derived metrics such as object detection confidence scores, number of recognized entities per frame, frame rates (FPS), and aggregated brightness or contrast levels can be structured as time series.

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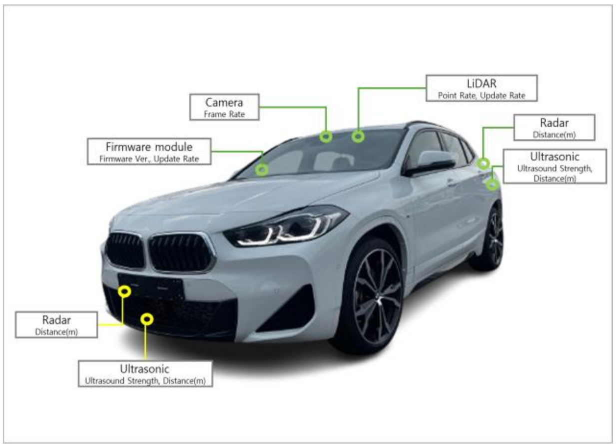


Figure 1. Sensor Configuration of an Autonomous Vehicle

These camera-derived signals contribute to the vehicle's environmental understanding. However, adverse weather conditions, varying lighting, lens contamination, or transmission issues can introduce noise or result in missing data. Such anomalies in camera-derived time series can impair perception and decision-making, thus requiring robust preprocessing and imputation techniques [5].

RADAR (Radio Detection and Ranging) sensors are primarily installed at the front and rear of the vehicle and use radio waves to measure the distance and relative speed of surrounding vehicles and obstacles. The time series data generated by radar sensors consist of measurements such as range, relative velocity, signal strength, and update frequency. However, factors like metal interference, reflection errors, and sensor aging can degrade distance measurement accuracy or cause signal loss [6].

LiDAR sensors are mounted on the roof or front of the vehicle to perform high-precision 3D scanning of the surrounding environment. The resulting time series data include point cloud information at each timestamp, intensity, laser scan rotation speed, number of scans, scan range, and scan angle. LiDAR is used for distance-based object detection and environment mapping; however, anomalies may occur due to factors such as external reflector characteristics, adverse weather conditions, and sensor misalignment [7].

Ultrasonic sensors are installed around the front and rear bumpers of the vehicle and are used to detect nearby obstacles during parking or low-speed driving. The time series data include distance measurements (range in meters), reflected signal strength, sensor activation/deactivation status, and delay time between signal transmission and reception. These data serve as input variables for parking assistance and automatic emergency braking systems. However, false detections or signal losses may occur due to foreign objects, sensor contamination, or narrow reflection angles [5].

The firmware module integrates data generated from individual sensors and transmits it to the vehicle's electronic control unit (ECU). The time series data recorded by this module include software version, system load status, sensor communication status (e.g., error occurrences), update intervals, and sensor synchronization status. This module plays a critical role in maintaining data consistency and temporal synchronization across sensors; therefore, internal processing delays or communication failures can adversely affect the overall system performance [5].

In summary, each sensor generates unique time series data that enable the autonomous driving system to assess the external environment and vehicle status in real time. However, various factors such as environmental conditions, hardware faults, and communication errors can induce anomalies in the time series data. Since these anomalies may lead to system malfunctions, early detection is essential. This study aims to improve the stability and reliability of autonomous driving systems by performing forecasting and anomaly detection based on such time series data.

III. ANOMALY FORECASTING BASED SYSTEM

The hybrid model, which combines the advantages of the traditional statistical ARIMA model and the deep learning-based Transformer, quantitatively captures the trend and stability of time series data while effectively learning complex nonlinear patterns and long-term dependencies. This architecture enhances forecasting performance by integrating both linear and nonlinear information. Fig. 2(a) illustrates the structure of the hybrid forecasting model combining ARIMA and Transformer [8].

A. *Hybrid model Ⅰ*

Hybrid Model I consists of a time series input processing unit, an ARIMA – Transformer forecasting module, and an output unit. As shown in Fig. 2(b), the input time series data is decomposed by ARIMA to estimate the linear components, and the generated residuals are fed into the Transformer along with the original data to learn nonlinear relationships.

The Transformer learns complex patterns within the input sequence based on positional encoding, multi-head attention mechanisms, and a feedforward neural network architecture, ultimately generating predictions for future time steps. The final forecast $\hat{y}_t$ is expressed as the sum of the linear prediction from ARIMA, the nonlinear correction from the Transformer, and the residual, as shown in the following equation.

This model separates linear and nonlinear information by assigning them to specialized models, and then fuses the final predictions through an additive approach, thereby achieving both improved forecasting accuracy and interpretability.

$$y_t = A_{t1} + B_t \tag{1}$$

$$\widehat{A_{t1}} = c + \cdots + \varphi_p y_{t-p} + e_t - \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} \tag{2}$$

$$B_t = y_t - \widehat{A_{t1}} \tag{3}$$

$$\widehat{B_t} = f(n_t, n_{t-1}, \cdots, n_{t-n}) + e_t \tag{4}$$

$$\hat{y}_t = \hat{A}_{t1} + \hat{A}_{t2} + \hat{B}_t \tag{5}$$

Here, y_t denotes the input time series data, A_{t1} represents the linear components input to the ARIMA model, A_{t2} denotes the linear components fed into the Transformer, B_t nonlinear indicates the nonlinear components, and e_t represents the residuals.

B. Hybrid model Ⅱ

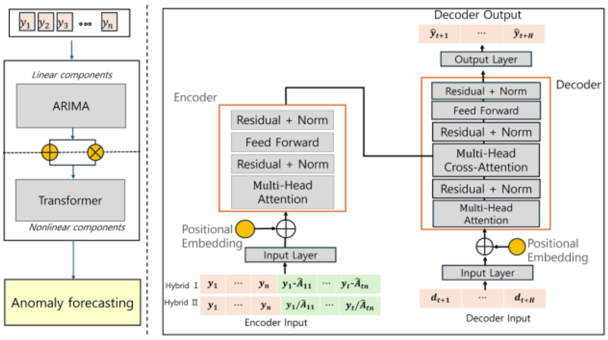
Hybrid Model II shares the same architectural components as Hybrid Model I but integrates the outputs of ARIMA and the Transformer in a multiplicative fashion. As illustrated in Fig. 2(c), ARIMA forecasts the linear component of the input time series, while the Transformer receives both the residuals and the original input sequence to learn the underlying nonlinear relationships. The final forecast is obtained by multiplying the outputs of the two models, forming a structure that synergistically captures both linear and nonlinear patterns.

$$y_t = A_{t1} * B_t \tag{6}$$

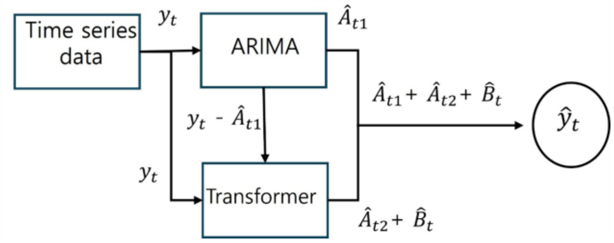
$$e_t = y_t / \widehat{A_{t1}} \tag{7}$$

$$\widehat{B_t} = f(n_t, n_{t-1}, \cdots, n_{t-n}) \bullet e_t \tag{8}$$

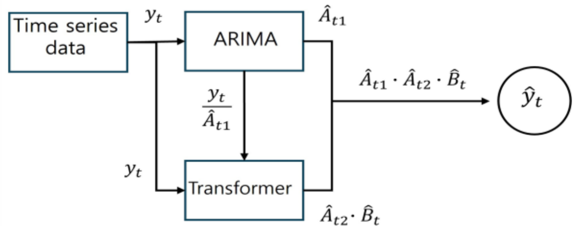
$$\hat{y}_t = \hat{A}_{t1} \bullet \hat{A}_{t2} \bullet B_t \tag{9}$$



(a) Overall System Architecture of the ARIMA-Transformer Hybrid



(b) Flow of ARIMA-Transformer Hybrid Ⅰ



(c) Flow of ARIMA-Transformer Hybrid II

Fig. 2. ARIMA–Transformer hybrid system [8].

Here, y_t denotes the input time series, A_{t1} represents the linear component estimated by ARIMA, A_{t2} indicates the linear input component provided to the Transformer, B_t refers to the nonlinear component, and e_t denotes the residual.

IV. EXPERIMENTS

A. Datasets and Preprocessing

This study utilizes a publicly available autonomous vehicle sensor metadata dataset [12], which is provided via a GitHub repository. The dataset includes time-series measurements and status information collected from various on-vehicle sensors, including LiDAR, RADAR, ultrasonic sensors, and cameras. Each time step contains both the sensor readings and operational status indicators.

In this study, anomalies in the sensor data were defined based on the **operation field**. Specifically, any time step for which the operation field was labeled as other than "normal" was considered an anomaly. These anomalous labels correspond to sensor malfunctions, out-of-range measurements, or unexpected environmental interferences such as occlusions, noise spikes, or communication errors. The dataset consists of 7,767 sequences, of which approximately 52.47% are labeled as anomalies.

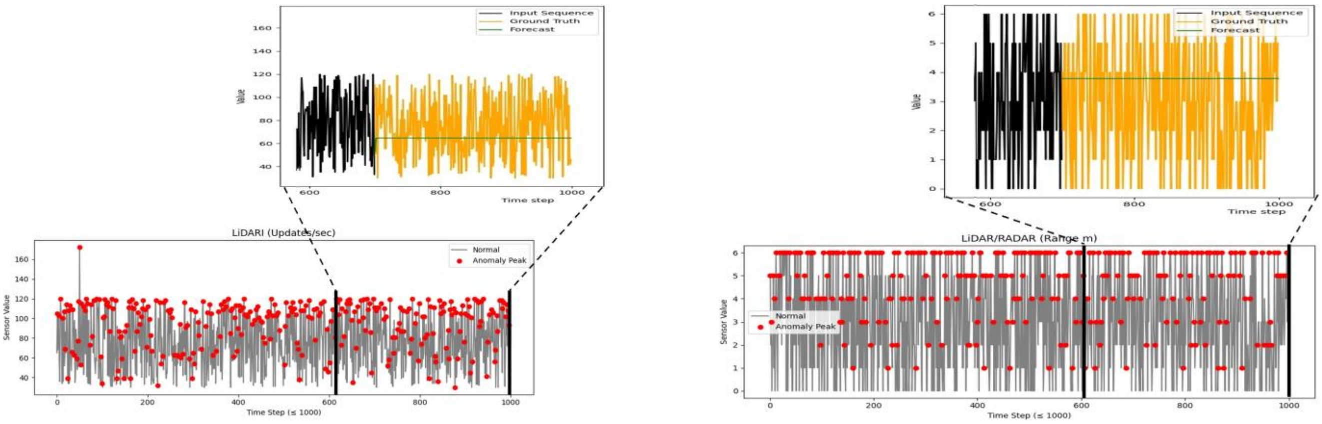
The models were trained and evaluated using the preprocessed test set, targeting the future 300 time steps for five selected sensor variables across a total of 6,768 time-series samples. Performance was quantitatively assessed using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Additionally, the predicted results were visually compared with the actual anomaly labels to further analyze the forecasting performance under both normal and abnormal operating conditions.

B. Forecasting Results

In this study, we conducted experiments to compare the In this study, experiments were conducted to compare the time-series forecasting performance of four models—LSTM, Transformer, and two hybrid architectures (Hybrid I and Hybrid II)—using autonomous-vehicle sensor data. Each input sequence consisted of 700 timesteps, followed by forecasting 300 future timesteps. The hybrid models were designed by integrating ARIMA predictions with the Transformer framework. Specifically, Hybrid I employed an additive combination, whereas Hybrid II adopted a multiplicative integration scheme.

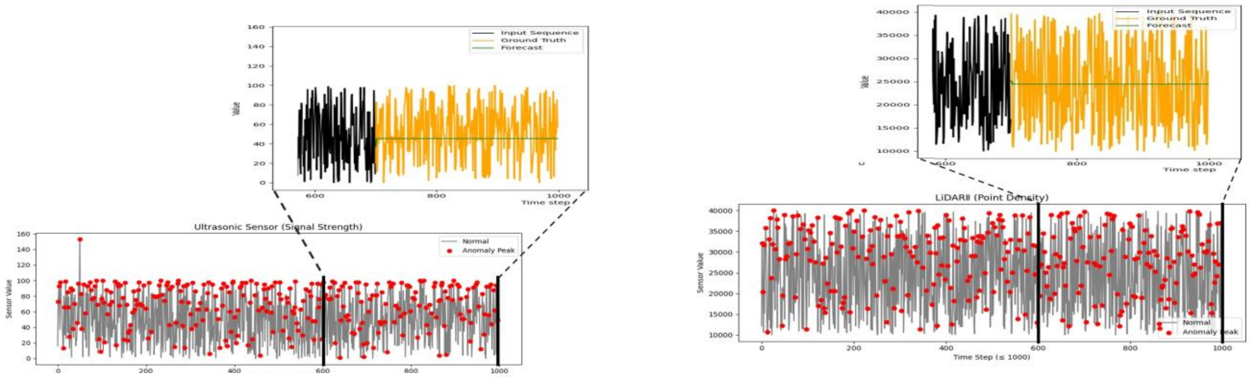
TABLE I. QUANTITATIVE COMPARISON OF FORECASTING PERFORMANCE UNDER ABNORMAL SENSOR DATA

System	MAE	RMSE	MAPE
LSTM Based	4953.83	5247.83	77.23
Transformer Based	4669.89	4980.99	76.48
Hybird I Based	3089.23	3361.28	72.72
Hybrid II Based	**2653.81**	**2945.06**	**72.61**



(a) LSTM Based / Lidar 1

(b) Transformer Based / Radar



(c) Hybrid 1 Based / Ultrasonic sensor

(d) Hybrid 2 Based / Ultrasonic sensor

Fig. 3. Example of time-series signals and forecasting results from major vehicle sensors (LiDAR, Radar, Ultrasonic, and Camera).

Fig. 3 illustrates representative examples of time-series data and forecasting results obtained from four major sensors (LiDAR, Radar, Ultrasonic, and Camera). Each subplot corresponds to a distinct sensor–model pair and aims to visualize the temporal characteristics and anomaly patterns of each sensor rather than to provide a direct model-to-model performance comparison. The black segments indicate input sequences (700 timesteps), the orange segments represent the predicted future sequences (300 timesteps), and the red dots denote detected anomalies. This figure enables intuitive understanding of how different sensor data behave under abnormal conditions and how forecasting models respond to such variations.

Table I presents the quantitative comparison of forecasting performance for all models using input data containing anomalies. Among the models, Hybrid II achieved the best performance, with a Mean Absolute Error (MAE) of 2,653.81, a Root Mean Square Error (RMSE) of 2,945.06, and a Mean Absolute Percentage Error (MAPE) of 72.61. These results indicate that the Hybrid II model provides stable and accurate forecasting under anomalous conditions, owing to its parallel integration of ARIMA and Transformer, which effectively captures both linear and nonlinear temporal dependencies. All error metrics were calculated based on normalized sensor values; therefore, MAE and RMSE are unitless, while MAPE is expressed as a percentage (%).

Hybrid I also exhibited improved performance compared with the single models, achieving MAE = 3,089.23, RMSE = 3,361.28, and MAPE = 72.72. In contrast, the Transformer and LSTM models showed relatively higher errors, with the LSTM model performing worst (MAE = 4,953.83, RMSE = 5,247.83), revealing the limitations of conventional recurrent-neural-network architectures. Comparing Hybrid II (best) and LSTM (worst) showed an approximate 46.44 % improvement in MAE.

V. CONCLUSION

This This study presents a novel application of the ARIMA–Transformer hybrid forecasting model to autonomous vehicle sensor time series data. The proposed architecture was optimized to accommodate complex driving environments and various anomaly scenarios. Experimental results using real-world data demonstrated that the Hybrid II model achieved superior performance in terms of Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), validating the effectiveness of combining linear and nonlinear modeling capabilities. These findings underscore the potential of the proposed model for robust forecasting in autonomous driving environments and its applicability to real-time anomaly detection. This work extends hybrid forecasting methodologies to the mobility domain, with future directions focused on generalizing the approach to a wider range of sensor modalities and enhancing computational efficiency.

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