Design of Traffic Electronic Information Signal Acquisition System Based on Internet of Things Technology and Artificial Intelligence

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Abstract

This study aims to devise a traffic electronic information signal acquisition system employing Internet of Things and artificial intelligence technologies, offering a novel approach to address prevailing challenges related to traffic congestion and safety. Initially, the hardware circuit for the high-speed signal acquisition control core is developed, leveraging Field-Programmable Gate Array technology. This facilitates wireless monitoring of signal acquisition. Subsequently, a comprehensive time signal acquisition system is formulated, encompassing modules for communication, acquisition, storage, adaptive measurement, and signal analysis. The geomagnetic acquisition module within this system is utilized for collecting geomagnetic signals, which are then translated into switch signals indicating the presence or absence of vehicles. These signals are subsequently transmitted to the geomagnetic signal processor. Experimental results pertaining to the signal acquisition system reveal a notable peak storage speed of 200KB/s, considering the utilization of one million sampling points. Across a series of tests, the maximum relative error of the obtained results ranges from 2.2% to 2.7%, underscoring the consistency and reliability of the measurements. In comparison to existing testing devices, the system exhibits heightened accuracy in test results, rendering it more apt for traffic signal acquisition applications. In conclusion, this study accomplishes the collection and dissemination of diverse traffic information, furnishing robust support for traffic control and ensuring safe operations.

Keywords

Artificial Intelligence, Internet of Things, Signal Acquisition System, Traffic Electronic Information.

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I. Introduction

PRESENTLY, urban transportation has faced significant and urgent challenges, including inadequate transportation infrastructure development, escalating traffic congestion, frequent traffic accidents, and a fundamentally flawed travel structure. These challenges profoundly impact the quality of life for urban inhabitants and hinder the sustainable advancement of cities. Traditional approaches, however, have limitations in effectively addressing these complexities. For example, conventional methods of acquiring traffic information rely predominantly on stationary sensor apparatus, restricting both the scope and immediacy of data collection. Additionally, established vehicle positioning technologies, such as the global positioning system (GPS), provide positional precision but are hindered by elevated energy consumption and cost, limiting their extensive integration within intelligent transportation systems (ITSs). However, vehicle positioning remains a crucial supporting technology for intelligent traffic information acquisition, holding vital practical significance [1].

Traffic information collection is a pivotal aspect of urban ITSs and the broader traffic domain. Effective traffic management and control heavily depend on acquiring precise and up-to-the-minute traffic information [2]-[4]. By leveraging contemporary digital technologies, such as the Internet of Things (IoT) and wireless sensor networks (WSNs), enables the automated acquisition, amalgamation, and transmission of critical data like vehicle positioning, traffic flow, and road occupancy. This technological integration facilitates the provision of more accurate and timely data, empowering urban traffic management and control endeavors. Furthermore, this technological approach plays a pivotal role in addressing persistent challenges related to traffic congestion and vehicular accidents. A WSN is a novel form of an intelligent application network capable of autonomously collecting, fusing, and transmitting data. It assumes a significant role in urban ITS, effectively addressing urban traffic problems [5]-[7]. The communication tree tracking method solves the target tracking challenge in the sensor network, ensuring efficient target tracking and minimal node communication costs.

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WSNs play a crucial role in acquiring traffic information, encompassing data on vehicle speed, traffic flow, road occupancy rates, and intersection traffic conditions [8]. Overcoming the limitations of traditional monitoring sensors, which hinder system scalability and network efficiency, WSNs offer enhanced information acquisition accuracy. The integration of multi-source traffic information further augments the efficiency of monitoring and management tasks, including parking management, electronic toll collection, energy conservation, and emission reduction. In certain scenarios, sensor nodes deployed randomly within an area can obtain location information through positioning technology [9], [10]. While the Global Positioning System (GPS) is the prevailing positioning technology, GPS receivers are unsuitable for sensor networks due to their high energy consumption and cost. Locating vehicles via WSN presents several advantages. Firstly, it ensures high tracking accuracy, as WSN nodes are widely distributed, providing a clear understanding of changes in the target's geographic location. Secondly, the tracking is reliable, allowing system configurations to be fine-tuned for detailed, accurate, and reliable motion information during target tracking. Thirdly, it offers efficient tracking, as existing WSNs can simultaneously monitor and track various sensors within a specified range. Lastly, it is easy to implement, as sensor nodes are cost-effective, compact, and easily portable, facilitating concealment [11]-[13]. Therefore, WSN target tracking offers significant concealment and feasibility.

This study attempts to deploy WSNs across various stages of information collection, transmission, processing, and feedback within ITS to modernize and elevate the current traffic electronic information signal collection. Initially, an analysis is conducted on the characteristics and requisites of intelligent transportation in the IoT environment. Building upon this analysis, a high-speed signal acquisition control core, based on a Field Programmable Gate Array (FPGA), is designed to enable wireless monitoring of signal acquisition. Subsequently, a real-time signal acquisition system is formulated to effectively gather and process signals, comprising communication, acquisition, storage, adaptive measurement, and signal analysis modules. Additionally, the geomagnetic acquisition module's key technology is thoroughly examined and designed. Anticipated outcomes include enhancing traffic electronic information signal collection effectiveness and elevating traffic information service quality within ITSs.

This study aims to design and implement a traffic electronic information signal acquisition system utilizing IoT and AI technologies. The primary aim is to address existing challenges related to urban traffic congestion and traffic safety. Specifically, the study seeks to achieve wireless monitoring and acquisition of traffic signals through the innovative application of geomagnetic signal acquisition and processing techniques. This initiative targets the enhancement of signal acquisition speed, precision, and efficiency to provide robust information support for traffic control, management, and safe operations. The overarching goal is to optimize traffic flow, alleviate congestion, elevate traffic safety, and offer pioneering resolutions for urban traffic issues. The devised traffic electronic information signal acquisition system is constructed based on IoT technology and artificial intelligence. The distinctiveness of this approach emerges from the fusion of IoT and AI to facilitate intelligent data collection and processing for accurate traffic signal monitoring, transcending the limitations of conventional methodologies. Furthermore, the system employs geomagnetic signal acquisition and conversion to acquire precise vehicle presence or absence information, thereby enabling high-precision vehicle monitoring and furnishing dependable data for traffic control and management. The system caters to a wide spectrum of traffic information, thereby furnishing robust information backing for traffic control and safety operations. Consequently, it contributes to optimizing traffic flow, mitigating traffic congestion, and enhancing overall traffic safety. The integration and application of IoT and AI technologies empower the proposed traffic electronic information signal acquisition system to accommodate diverse scenarios and environments, showcasing commendable applicability and adaptability.

The structure of this study unfolds in the following sections: Section I, designated as the introduction, provides an overview of prevalent issues and challenges in urban transportation. It emphasizes the limitations of conventional approaches, underscores the significance of employing IoT and AI technologies to address transportation predicaments, and outlines the research objectives. Section II, comprising the literature review, conducts an examination of pertinent research domains. It delves into the application of IoT technology within intelligent transportation and scrutinizes the constraints inherent in existing methodologies. Section III, encompassing the research methodology, expounds upon the pivotal methodologies and technologies leveraged to tackle urban transportation issues. This section covers topics such as IoT-supported intelligent transportation, FPGA-based high-speed signal acquisition, the underpinning principles of geomagnetic signal acquisition, and the design of an adaptive, real-time signal acquisition system for traffic. It culminates in the formulation and design of a real-time signal acquisition system. Section IV, titled "Experimental Design and Performance Evaluation," delineates the orchestrated experimental procedures, including data acquisition and performance assessment. It further elucidates the test outcomes and the system's performance prowess. Section V, denominated as "Conclusion," provides a synthesis of the research content and methodologies encapsulated in the thesis. This segment culminates in overarching conclusions, and avenues for future research are envisaged.

II. Literature Review

A. Research Progress and Applications of AI

With the rapid evolution of AI technology, its integration into intelligent transportation has grown steadily. Akhtar and Moridpour (2021) provided a comprehensive synthesis of existing research on traffic congestion anticipation, incorporating various AI approaches with a prominent focus on diverse machine learning models. The authors meticulously categorized these models, offering a succinct overview of their merits and drawbacks [14]. Abduljabbar et al. (2019) elucidated the swift progress of AI within the transportation domain, highlighting its versatile applications in overcoming transportation challenges. The study specifically underscored AI's potential in data analysis, predictive modeling, and optimized decision-making, thereby enhancing transportation system efficiency, reliability, and sustainability [15]. Wu et al. (2022) explored AI's role in the context of smart city construction, particularly its current standing in intelligent transportation infrastructure. The research delved into scrutinizing diverse dimensions such as spatial typology, functional classifications, and facility utilization. The findings illuminated the substantial advantages of AI technology in classifying and administrating transportation infrastructure [16]. In summary, numerous AI methodologies have found widespread application in fields encompassing traffic flow projection, signal optimization, and accident forewarning. These methodologies possess the capability to refine and elevate transportation systems. Their potency lies in their adeptness at scrutinizing extensive traffic datasets, distilling pertinent features, and executing astute decisions.

B. Research Progress and Applications of IoT

Recently, the rise of IoT technology has opened new avenues for advancing ITSs. Wang and Ma (2022) conducted a focused investigation on the recognition and classification of stationary vehicles and seat belts within intelligent IoT-based traffic management systems. An innovative identification algorithm was introduced for the surveillance of stationary vehicles, leading to a substantial enhancement in detection accuracy compared to conventional background differential algorithms. Moreover, a proficient driver localization algorithm was formulated for driver seatbelt detection, uniting a target detection algorithm with a streamlined network structure, effectively elevating localization precision [17]. Ushakov et al. (2022) gathered insights from multiple European transportation agencies concerning public transportation. Through a comprehensive case study, they probed the far-reaching effects of IoT on the global transportation system. The study illuminated IoT's expansive potential within transportation, foreseen to amplify both system efficiency and safety [18]. Muthuramalingam et al. (2019) underscored the pivotal role of IoT solutions within the worldwide ITS, particularly in the domain of intelligent transportation marked by vehicle-to-vehicle communication. The authors delineated how IoT-based ITS can automate transport across railways, roadways, airways, and oceans, augmenting the logistics of cargo transportation, monitoring, and delivery, consequently enhancing customer experiences [19]. By interconnecting sensors, devices, and networks, real-time aggregation, transmission, and analysis of transportation data can be effectively achieved. IoT technology seamlessly amalgamates various facets of the transportation system, fostering comprehensive data utilization and augmenting traffic management intelligence.

C. Research Review

The aforementioned studies exemplify the utilization of AI and IoT technologies in intelligent transportation, approaching the subject from diverse vantage points. However, a dearth of research specifically focuses on the traffic signal acquisition system in isolation. Drawing from the principles of fuzzy control, this study introduces a fresh methodology to refine the traffic information acquisition system, aiming to enhance both the efficiency and the intelligence of traffic management.

III. Research Methodology

A. Intelligent Transportation Supported by IoT Technology

Entities need to communicate with each other, giving rise to the necessity for machine-to-machine (M2M) communication. Utilizing wireless short-range communication technologies is a viable approach, such as Wi-Fi, Bluetooth, and ZigBee, or large-scale mobile communication technologies, including World Interoperability for Microwave Access, Long Range, Sigfox, CAT M1, NB-IoT, Global System for Mobile Communications, General Packet Radio Service, the 3rd Generation Telecommunication, the 4th Generation Telecommunication, Long Term Evolution, and the 5th Generation Telecommunication [20]. Maintaining the affordability of IoT devices is paramount, especially considering their extensive usage across various daily life applications. Furthermore, IoT devices must possess the capability to fulfill basic tasks such as data collection, M2M communication, and even pre-processing data according to application requirements.

Intelligent traffic research represents a promising avenue for addressing urban traffic challenges. Advanced urban rail transit systems play a crucial role in providing residents with access to both dynamic traffic data and static information [21], [22]. Public transportation offers significant advantages, including substantial passenger capacity, enhanced transportation efficiency, minimal energy consumption, and low transportation costs. Consequently, urban informatization becomes a vital focus of research. IoT serves as a robust platform for intelligent transportation, facilitating the exchange of vehicle information through the network without human intervention. This enables intelligent transmission and sharing among vehicles. Navigation and route optimization stand out as pivotal aspects of intelligent transportation. Applications can leverage data from a user's mobile device or a roadside unit at a designated location to estimate traffic congestion and propose optimal route options. This approach minimizes travel time, thereby mitigating vehicle emissions and reducing energy consumption. Furthermore, a proposal is made for the introduction of smart streetlights equipped to detect traffic conditions and adjust illumination accordingly, aiming to contribute to energy conservation [23]-[25].

Fig. 1 shows the architecture of the IoT-based ITS.

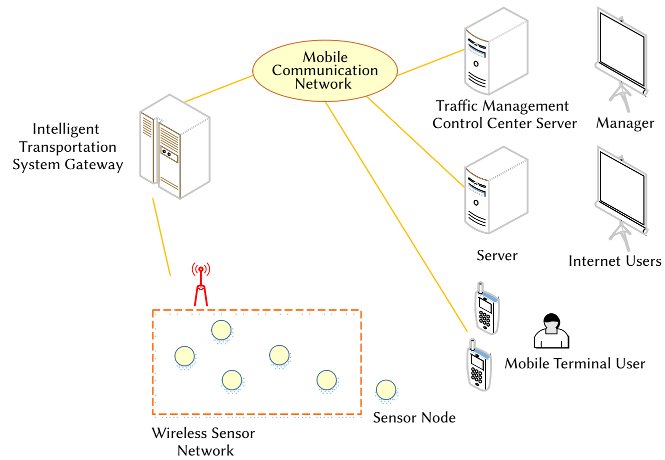

Fig. 1. IoT-based ITS architecture.

Intelligent transportation WSN is a purpose-driven wireless self-organizing network system, typically composed of multiple data convergence points and an array of sensor nodes dispersed throughout the ambient surveillance region. These nodes incorporate radio transponders, sensors, embedded processors, and more, enabling them to acquire, process, and transmit traffic data [26]. Network simulation software is employed to make these models functional, allowing a vehicular ad hoc network to utilize vehicle motion models [27]. Different scenarios are generated prior to the simulation, and the emulation program analyzes these scenarios based on a predefined path layout. Special applications in vehicular communication impose essential interaction requirements, facilitating communication between the two domains. Fig. 2 illustrates an isolated method of interaction between the transportation emulation program and the network simulation software.

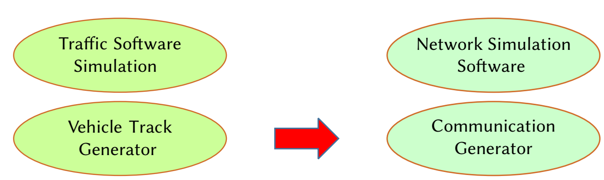

Fig. 2. An isolated method of interaction between traffic simulation software and network simulation software.

The two simulators are seamlessly integrated into a unified system to facilitate comprehensive interaction between the network and traffic simulation software. A straightforward collaboration between the web and mobile domains compensates for the absence of a protocol. The embedded approach provides the advantage of a streamlined and efficient interaction between the network and mobility models. This method utilizes validated vehicle motion models and strictly adheres to standard protocols.

B. FPGA-Based High-Speed Signal Acquisition

While high-resolution imagery is not obligatory for traffic sign detection, it does enhance the detection range in the Advanced Driver Assistance System (ADAS). Contemporary high-end processors boast sufficient computing power for executing these tasks, albeit at the cost of significant energy consumption [28]-[30]. Nevertheless, low power consumption and reliability are paramount for embedded systems like ADAS. In this context, FPGAs emerge as a potential solution to this challenge, as they can dynamically adjust their hardware to meet the current requirements of the application.

Information collection and manipulation systems have broad applications in metering and regulating systems. The information collection process involves measuring diverse electrical phenomena, including sound, pressure, temperature, current, or voltage. Various types of sensors are employed to measure heterogeneous parameters, such as velocity, viscosity, pressure, temperature, friction level, and vibration [31]. Chip-integrated information collection systems efficiently consolidate extensive functionalities onto a single compact chip, resulting in cost reduction, size diminution, and enhanced performance. Utilizing an FPGA network to govern the design module enables multi-channel data processing, which minimizes hardware requirements and enhances reconfigurability.

The NI LabVIEW FPGA Module extends the capabilities of the LabVIEW graphical development platform, making it particularly suitable for FPGA programming due to its explicit representation of parallelism and data streams. The modules responsible for multi-channel data collection and processing are executed within a dedicated NI cRIO device featuring an embedded FPGA. The design and implementation of the FPGA are carried out using the Project Explorer window. It involves creating FPGA target.vi and Host.vi, as well as configuring the relevant hardware before initiating the project implementation. The Target.vi serves as the FPGA target, accessing the desired number of inputs and selecting the input ports of the block. It determines the data type, memory size, and procedures for data reading and writing. Once compiled, it generates the bit file, which can be loaded into Host.vi. Fig. 3 illustrates the six-step FPGA design process, culminating in the transference of generated files to the FPGA for test verification in the final stage of the design.

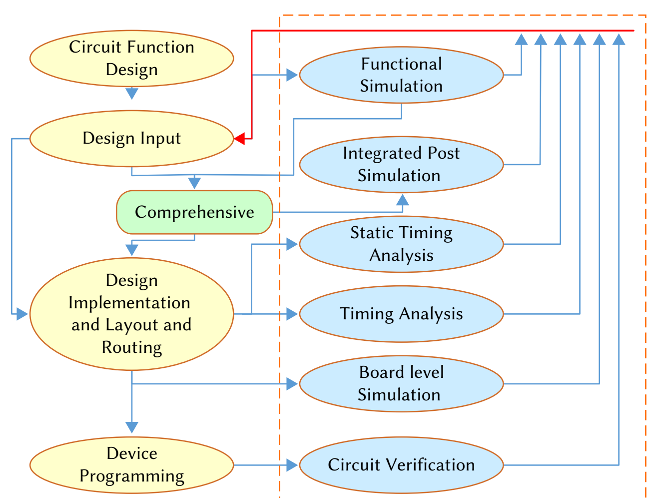

Fig. 3. FPGA design process.

C. Realization Principle of Geomagnetic Signal Acquisition

Geomagnetic detection represents an innovative vehicle detection technology involving the sensing of the magnetic field within the geomagnetic field using an anisotropic magneto-resistive sensor to ascertain the vehicle's condition. Currently, geomagnetic vehicle detectors predominantly rely on wireless transmission, offering advantages such as high detection accuracy, stability, reliability, and ease of installation and maintenance, making them highly sought after in the market. Integrating WSN and geomagnetic sensors, the traffic flow acquisition system collects vehicle induction data through these sensors. Users can access real-time road traffic flow information in the background through centralized management. Geomagnetic sensor detection technology is widely recognized as one of the most effective traffic data collection methods.

The presence of ferromagnetic substances within the vehicle influences the geomagnetic signal in the surrounding area, causing a distortion in the earth's magnetic field lines [32], [33]. When a vehicle passes near the sensor of the vehicle detector, the sensor sensitively perceives the signal change and extracts relevant information about the detected target through signal analysis. The WSN-based geomagnetic signal acquisition system offers ease in construction and maintenance, enabling real-time monitoring of traffic flow conditions [34]-[36]. Within geomagnetic signal acquisition, the anisotropic magnetoresistance effect demonstrates directionality. Equation (1) describes the relationship between the magnitude of the resistance value of a metal with anomalous reluctance effects between the bias current and the direction of the magnetic field.

$$R(\theta) = R1 \sin 2\theta + R2 \sin 2\theta \quad (1)$$

In Equation (1), θ stands for the angle between the magnetic field and the current direction; $R1$ and $R2$ represent the resistance values of the metal when the magnetic field direction and the current direction are parallel and perpendicular to each other, respectively. Fig. 4 illustrates the principle of the magnetoresistance effect.

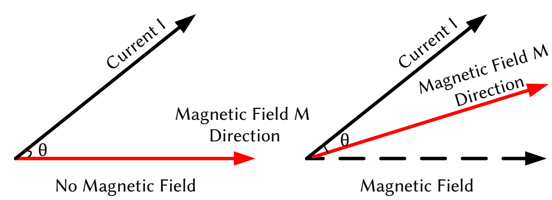

Fig 4. Principle of the magnetoresistance effect.

The geomagnetic signal collector is employed to capture geomagnetic signals and transform them into switch signals, indicating the presence or absence of a vehicle. These signals are then transmitted to the geomagnetic signal processor. Vehicle induction data is conveyed through the multi-hop transmission mechanism of the WSN, and the geomagnetic sensor is utilized for collecting the vehicle induction data. Real-time road traffic flow information is accessible to users through centralized background management. Compared with traditional traffic flow collection systems, the WSN-based traffic flow monitoring system is advantageous for its ease of construction and maintenance, facilitating real-time monitoring of traffic flow conditions. Fig. 5 illustrates the network topology of the geomagnetic data acquisition system.

The geomagnetic data acquisition system is built around an optimized single-chip microcomputer (SCM), serving as the hardware core. Discrete components are replaced with integrated circuit chips to enhance the operational reliability of the system. The core is the SCM P89C668, and its peripheral devices are configured to form a comprehensive hardware structure. This structure includes a liquid crystal display, keyboard, communication interface, non-volatile data memory, 16-bit A/D conversion, clock chip, GPS receiving module, and wireless modem. The communication interface employs the MAX202 chip for TTL and RS232 level conversion. On the transmitter side, the interface connects to the data acquisition unit, collects data, processes it, and transmits it to a modem via a microcontroller. At the receiving end, the port receives remote data through the modem. Subsequently, the SCM transmits the processed data to the computer. While the actual local geomagnetic field may vary with the environment, positional differences and surrounding structures have minimal impact on the magnetic field length in the short range and can be disregarded. Assessing the geomagnetic field distribution is necessary for determining variations in magnetic field length over long distances. Disparities between the calibration environment and operating environments have the most significant effect on the true local geomagnetic field. Over the long term, the geomagnetic vehicle detector industry is expected to continue improving, with signaling and parking management serving as key drivers for future development.

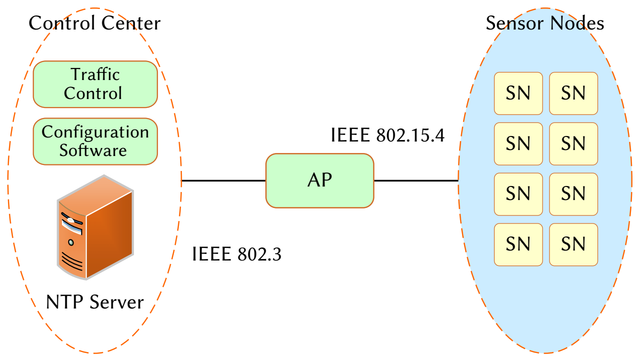

Fig 5. Network topology of the geomagnetic data acquisition system.

D. Adaptive Measurement of the Traffic Real-Time Signal Acquisition System

Transportation control plays a pivotal role as a technological tool in alleviating traffic congestion, managing traffic volumes, and reducing emissions. Its advancement is closely intertwined with progress in system science, information technology, and computer technology. The self-adaptive control system stands out by adjusting signal timing parameters in real-time, aligning with the manager's control objectives and the characteristics of intersection transportation flow. In comparison to timing and driving control methods, this system more effectively utilizes the entire road network's throughput, enhancing transportation efficiency. Current transportation management systems, employing inductive loop detectors and other sensing devices, are constrained in the extent of transportation information they collect. However, with the ongoing development of wireless communication technologies and vehicle-to-vehicle/vehicle-to-infrastructure systems (referred to as vehicle-to-everything), the optimization of urban transportation networks through the collaboration of traffic signal control and driving behavior regulation has become feasible [37]. This study introduces an optimization method that adjusts the vertical position of the oscilloscope over time using classic fuzzy control theory based on the measured traffic signal amplitude. This approach facilitates adaptive signal measurement.

The fundamental concept behind fuzzy control is to employ a computer to replicate human control experiences, often conveyed through language using fuzzy control rules [38], [39]. The primary factor contributing to the substantial success of the fuzzy controller (FC) is its rule-based nature. It directly applies language-based control rules and does not necessitate the development of a precise mathematical model of the controlled object during the design phase. Consequently, its control mechanism and strategy are easily comprehensible and accessible.

Firstly, the fuzzy set is defined. Given a domain of discourse, the mapping from U to the unit interval [0, 1] can be referred to as a fuzzy set on U, which can be expressed as in Equation (2).

$$\mu_A: U \rightarrow [0,1] \tag{2}$$

The membership function of each fuzzy set A on U is $\mu_A(u_i)$. A can be expressed as Equation (3).

$$\sum_{i=1}^{n} \mu_A(u_i)/u_i \tag{3}$$

Equation (4) indicates the arbitrary fuzzy set of U.

$$A = \int_U \mu_A(u)/\,u \tag{4}$$

Several membership functions commonly used in FCs are described as the followings.

(1) Trapezoidal membership function in Equation (5) and (6):

$$f(x,a,b,c,d) = \begin{cases} \frac{x\cdot a}{b\cdot a} & a \le x \le b \\ 1 & b \le x \le c \\ \frac{d\cdot x}{d\cdot c} & c \le x \le d \\ 0 & x < a, x > d \end{cases} \tag{5}$$

$$a \le b \le c \le d \tag{6}$$

(2) Triangular membership function in Equation (7) and (8):

$$f(x,a,b,c) = \begin{cases} \frac{x\cdot a}{b\cdot a} & a \le x \le b \\ \frac{c\cdot x}{c\cdot b} & b \le x \le c \\ 0 & x < a, x > c \end{cases} \tag{7}$$

$$a \le b \le c \tag{8}$$

(3) Gaussian membership function in Equation (9):

$$f(x,\sigma,c) = e^{-\frac{(x-c)^2}{2a^2}} \tag{9}$$

where c refers to the midpoint position of the Gaussian function, and the width of the Gaussian function depends on the value of σ.

This study leverages the concepts and techniques of fuzzy control to optimize the vertical positioning of the oscilloscope, enabling adaptive measurement of traffic signals to suit varying signal amplitudes. Initially, a set of fuzzy sets is defined, encompassing categories like "small," "medium," and "large" to signify distinct signal amplitude ranges. Subsequently, a corresponding collection of fuzzy rules is devised for each fuzzy set, delineating how adjustments to the oscilloscope's vertical position should be enacted in response to signal amplitudes within specific ranges. These rules can be formulated based on domain experts' insights, accrued knowledge, and signal acquisition requisites. The activation level of each fuzzy set is then ascertained through a fuzzy inference process, which hinges on real signal amplitude values. This inference entails employing fuzzy rules that map actual signal amplitudes to the activation degree of the corresponding fuzzy set. Lastly, the fuzzy output derived from the fuzzy reasoning process is transformed into a definitive control operation, specifically the manipulation of the oscilloscope's vertical position. This step may involve employing defuzzification techniques inherent to fuzzy control, such as using the average or maximum value of the fuzzy output as the ultimate control operation.

Based on the above analysis, this study formulates an effective digital model. The input to the FC consists of the first and second significant digits of the signal amplitude. The effective digit denoted as $f(x)$ of the signal amplitude can be expressed as Equation (10).

$$f(x) = \begin{cases} 10f_1(x) + f_2(x) & f_1(x) = 1 \\ f_1(x) + 0.1f_2(x) & other \end{cases} \tag{10}$$

Table I lists the effective figures obtained through function calculation.

TABLE I. Relationship Between Input Effective Figures and Signal Amplitude

Serial number	Signal amplitude (v)	Effective number
1	35.4	3.5
2	1.64	16
3	0.893	9.0
4	0.430	4.3
5	0.133	1 3
6	0.068	6.8

Fig. 6 reveals the relationship between the digital gear and the significant digits of the signal amplitude.

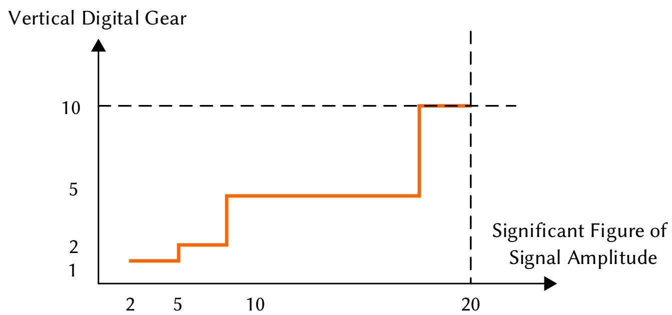

Fig 6. Relationship between the digital gear and the effective figure of the signal amplitude.

This study employs a set of representative signal parameter test data to assess and validate the program's output results. The computed results are displayed in Table 2, clearly demonstrating that the program has successfully achieved its intended functionality. This outcome confirms the feasibility and effectiveness of the fuzzy control algorithm.

TABLE II. Relationship Between Signal Amplitude and Vertical Scale

Signal amplitude (V)	Digital gear	Range gear (V)	Vertical gear (V/div)	Range (V)
0.010	5	0.001	0.005	0.02
0.016	5	0.001	0.005	0.02
0.4	1	0.1	0.1	0.4
1.63	5	0.1	0.5	2
1.92	10	0.1	1	4
2.5	1	1	1	4
7.22	2	1	2	8
22.5	1	10	10	40

IV. Experimental Design and Performance Evaluation

A. Experimental Materials

The principal aim of this experiment is to empirically validate the performance and efficacy of the proposed system. A comprehensive set of experiments has been carefully designed to scrutinize the system's performance across diverse scenarios, with a particular focus on temporal aspects related to acquisition tasks and storage velocity. Throughout the experimental process, the time required for signal transmission and code execution has been emulated to reflect real-world conditions. The system's storage speed has been rigorously assessed using a finely calibrated oscilloscope set to a resolution of 1ms/div to minimize potential testing inaccuracies. A meticulous approach has been adopted, synthesizing the final performance evaluation results by averaging outcomes from multiple experimental trials.

The experimental data used here consists of authentic signal data, including information about acquisition task duration, storage velocity, and the system's relative error. This empirical data serves a dual purpose: conducting a comprehensive assessment of the system's performance across varied scenarios and substantiating the system's dependability and precision.

B. Experimental Environment

The experiment is conducted within the premises of a high-speed railroad technical test station, replicating a real-world testing environment. In this setting, the test station is tasked with capturing equipment signals while potentially facing instances of high-amplitude transient pulse interference. These challenges serve as rigorous tests for evaluating the system's performance robustness and stability.

C. Parameters Setting

During the experimental phase, the oscilloscope's sampling rate is set at 1GSa/s to ensure an ample number of sampling points for proficient signal acquisition. In alignment with distinct testing scenarios, the system's adaptive parameters are systematically tuned through diffusion control, stepping control, and the dichotomous search algorithm, thus achieving the objective of adaptive measurement. Simultaneously, an assessment of the system's maximum relative errors is conducted across varying vertical resolutions using multiple sets of experimental data, facilitating an evaluation of the system's measurement accuracy and stability.

D. Performance Evaluation

1. System Verification and Index Analysis

The time required for the test system to complete a data collection task includes the time consumed during signal transmission to the PC and the time spent executing specific code instructions (adaptive adjustment). The system's storage speed is assessed at the oscilloscope's 1ms/div setting to prevent test inaccuracies, and the average of multiple test results is considered the final outcome. The test outcomes are depicted in Fig. 7. It is observable that the system's individual acquisition time increases as the oscilloscope's sampling points increase. The system's peak storage speed can reach 200KB/s when the number of sampling points reaches 1M. In the research conducted by Jin and Ma (2019) [40], a Constrained Markov Decision Process model is utilized to depict agent decisions, thereby optimizing multiple strategic objectives. The outcomes of their study closely align with the results presented in this study.

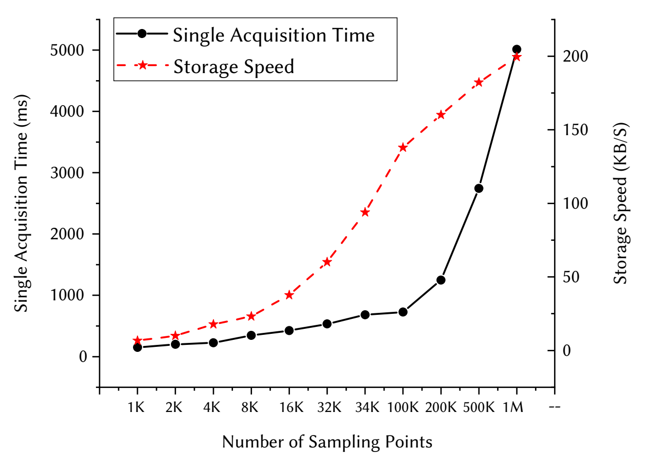

Fig 7. Relationship between collection points and single collection time.

2. Analysis of System Errors

Currently, high-speed railway technology test stations require digital recorders to capture equipment signals. Typically, the test subject installs the equipment at a designated test location, and personnel departs the area after configuring various parameters. The test equipment must achieve long-term continuous acquisition and automated signal storage. Given the presence of high-amplitude transient pulse interferences on railways, measurement parameters must be dynamically adjusted based on emergency conditions to ensure measurement accuracy and adaptive measurement of burst signals. It is recognized that digital oscilloscopes can achieve sampling rates of up to 1GSa/s. In this context, sufficient sampling points can be captured; hence, the test system's sampling rate is set to 1GSa/s. For signals being tested within the oscilloscope's current testing apparatus, adaptive parameters of the testing device are adjusted through diffusion control. Conversely, when the signal to be tested is not within the current testing device, the adaptive parameters are established using step control and a binary search algorithm. The maximum relative error of the system across multiple test configurations is computed through numerous sets of experiments. Table 3 presents a summary of the specific outcomes. After several tests, it is apparent that the maximum relative error of the test outcomes remains below ± 2.7%. This system attains more precise test outcomes in comparison to existing testing equipment, rendering it better suited for application in the collection of traffic signals. Chen and Zhang (2022) [41] developed a traffic flow prediction model utilizing the Deep Belief Network (DBN) algorithm. By collecting and pre-processing historical traffic flow data and incorporating multiple Restricted Boltzmann Machines in the DBN, they established a generative model for training. This procedure adds further validation to the reliability of the results presented in this study.

TABLE III. Maximum Relative Error at Different Vertical Gears

Vertical gear (V/div)	Minimum voltage increment (mV)	Current range (V)	Measuring range (V)	Maximum relative error (±)
0.002	0.08	0.008	0.0035~0.0075	2.2%
0.005	0.2	0.02	0.0075~0.018	2.6%
0.01	0.4	0.04	0.018~0.036	2.2%
0.02	0.8	0.08	0.036~0.075	2.7%
0.05	2	0.2	0.075~0.176	2.3%
0.1	4	0.4	0.176~0.362	2.2%
0.2	8	0.8	0.362~0.745	2.6%
0.5	20	2	0.745~1.73	2.3%
1	40	4	1.73~3.60	2.2%
2	80	8	3.60~7.45	2.2%
5	200	20	7.45~17.3	2.7%

V. Discussion

This study successfully designed and implemented a traffic electronic information signal collection system based on IoT technology and artificial intelligence. By leveraging FPGA technology, the hardware circuitry for the high-speed signal acquisition control core was developed, enabling wireless monitoring of signal collection. This innovative design achieves wireless monitoring of signal collection and imparts efficient data processing capabilities to the system, ensuring stable operation even in complex traffic environments. As detailed in this study, the time signal acquisition system encompasses multiple modules: communication, acquisition, storage, adaptive measurement, and signal analysis. The magnetic field acquisition module stands out for its effective collection of magnetic field signals and their conversion into switch signals, indicating the presence or absence of vehicles. This design enhances not only the practicality of the system but also its adaptability to dynamically changing traffic conditions.

The experimental results demonstrate the excellent performance of the system designed in this study in data storage and processing, achieving a significant peak storage speed of 200KB/s. Considering the substantial volume of data the system needs to handle, this achievement undoubtedly showcases the system's outstanding capabilities. In a series of tests, the maximum relative error of the obtained results ranged from 2.2% to 2.7%, further emphasizing the consistency and reliability of the measurements. Compared to existing testing devices, the system designed in this study exhibits higher accuracy in test results, rendering it more suitable for collecting traffic signals. It is noteworthy that the designed system can collect and process traffic information in real-time and be able to self-adjust and optimize based on changes in traffic conditions. This feature grants the designed system strong adaptability and flexibility, allowing it to maximize utility in various traffic environments.

In conclusion, the incorporation of AI technology, specifically fuzzy control, into traffic signal acquisition systems has proven to be a valuable strategy for enhancing system precision. A comprehensive literature review conducted by Ranyal et al. (2022) on road condition monitoring, spanning from 2017 to 2022, explored various approaches, innovative contributions, and limitations in the field. The authors underscored the importance of smart sensors and data acquisition platforms while addressing challenges in AI technology development. Their analysis provided valuable insights outlined directions and perspectives for future research in the realm of road condition monitoring [42]. In summary, a growing body of evidence suggests that the integration of AI into intelligent transportation and smart cities holds the potential to significantly optimize road conditions, thereby advancing the overall transportation system.

The algorithm proposed in this study facilitates the development of the hardware circuit for the high-speed signal acquisition control core, employing FPGA technology. This innovative design enables the system to achieve wireless monitoring of signal acquisition and demonstrates efficient data processing capabilities. Distinguished from other state-of-the-art algorithms, the proposed algorithm greatly emphasizes hardware-level optimization and innovation, thereby enhancing the system's overall performance and stability. The proposed algorithm incorporates a geomagnetic collection module that effectively gathers geomagnetic signals, transforming them into switch signals indicating the presence or absence of vehicles. This design allows the system to dynamically adapt to changing traffic environments, thereby increasing its practicality. In contrast to other advanced algorithms that typically rely on traditional sensors or cameras for data collection, the algorithm presented here is characterized by its innovation and adaptability. The study successfully achieves the collection and sharing of various traffic information, providing robust information support for traffic control and safe operations. However, the system still possesses certain limitations, such as potential performance bottlenecks when dealing with large-scale complex data. Future research directions will focus on optimizing system performance and enhancing data processing capabilities to achieve more efficient and accurate traffic information collection and processing.

VI. Conclusion

1. Research Contribution

Deploying various intelligent technologies and equipment to advance the digitization, interconnection, and intelligence of transportation defines intelligent transportation. Network connectivity emerges as a critical application integral to the evolution of intelligent transportation, with the IoT playing a pivotal role in seamlessly connecting all components of transportation. This technology has the potential to revolutionize the traffic industry by optimizing the efficient utilization and management of traffic information, reinforcing traffic oversight, and elevating traffic services. It encompasses information collection, policy control, output execution, data transmission, and communication between subsystems. Experimental results demonstrate that, with a sampling point count of 1M, the system achieves a maximum storage speed of up to 200KB/s. Throughout numerous tests, the peak relative error in test outcomes ranges from 2.7% to a mere 2.2%. Notably, the test results from this system showcase enhanced accuracy compared to existing testing equipment, making it more suitable for traffic signal acquisition applications. This study affirms that the real-time signal acquisition system within the IoT environment can promptly gather, analyze, and process collected signals. An intelligent traffic signal optimization control system is established through the integration of the intelligent collection system and the comprehensive analysis of big data.

2. Future Works and Research Limitations

This study introduces the design and experimentation of a traffic electronic information signal acquisition system based on IoT and AI technologies. However, several limitations should be acknowledged. The experiments primarily focus on validating the performance of the signal acquisition system, particularly regarding storage speed and relative error. Nevertheless, the experimental scenarios and datasets are relatively limited, potentially not capturing the entirety of real-world traffic situations and intricacies. The study predominantly emphasizes the design and performance evaluation of signal acquisition systems without comprehensive integration within the broader context of ITSs. Actual ITS scenarios often involve additional factors such as traffic flow management and incident prediction. Future research endeavors could explore the integration of this traffic electronic information signal acquisition system with other ITS components, such as traffic flow management and vehicle behavior prediction. This integration could lead to more comprehensive traffic management and optimization, addressing a broader spectrum of challenges in the field. Although this study successfully attains a noteworthy peak storage speed of 200KB/s, the system can face performance bottlenecks when confronted with extensive and intricate datasets. The design and optimization strategies are primarily tailored to specific traffic scenarios, necessitating further validation of the system's adaptability to diverse contexts. Subsequent research endeavors should prioritize augmenting the algorithm's generalization capabilities, thereby enabling it to adeptly accommodate a broader spectrum of traffic scenarios.

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