A SURVEY ON INTERNET OF VEHICLES SYSTEMS IMPLEMENTED USING INTERNET OF THINGS WITH ARTIFICIAL INTELLIGENCE

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Abstract
The Internet of Things (IoT) is a network that links all items that have computational and communication capabilities and allows them to interact to complete a task. Automobiles, buildings, and other elements equipped with sensors, actuators, and gateways can now be connected via the Internet of Things. The internet of things (IoT) includes a subset called the internet of vehicles (IoV) (IoT). The Internet of Vehicles (IoV) is a network that connects things, vehicles, and their surroundings to transport data and information between networks. The Internet of Vehicles (IoV) is a crucial component of the Internet of Things (IoT) (IoT). In the Internet of Vehicles (IoV), the communications exchanged between cars, infrastructure, and wearables must be reliable and delivered quickly. In this paper, we provide an overview of IoV systems that use IoT, as well as a list of promising research areas.
Keywords: Internet of things, Internet of vehicles, Edge computing

Introduction

The number of automobiles on the road has recently been expanding at an exceptional rate, and it is expected to reach 2.8 billion by 2036[1]. Several concerns, such as traffic congestion and road accidents, have arisen as a result of such a significant growth in the number of people. According to the World Health Organization, road accidents are the leading cause of death among people aged 5–29 years old, with approximately 1.3 million people killed on the road each year [2]. As a result, new and complex traffic control technologies are in great demand. The ongoing expansions and breakthroughs in connected cars are transforming the concept of transportation by improving intelligent transportation systems (ITS) to increase traffic throughput and road safety by lowering traffic congestion and the danger of road accidents[3,4]. These systems rely on the massive amount of sensor data generated by embedded sensors in contemporary automobiles to be acquired, analyzed, and processed. These sensors communicate with other internal sensors and sensors in their immediate surroundings by employing the Internet of Things (IoT) concept, in which interconnected objects share data about themselves and their environment to build intelligent networks [5]. In 2025, it is anticipated that 152,200 IoT devices will connect to the Internet each minute, bringing the total data volume to 73.1 ZB [6, 7].

Network model: The IoV is an emerging intelligent network that provides safety and comfort to the public. It consists of a centralized Trusted Authority (TA), a Traffic Management Cloud Server (TMCS), a number of Roadside Units (RSUs), and automobiles with On Board Units (OBUs) (OBU).

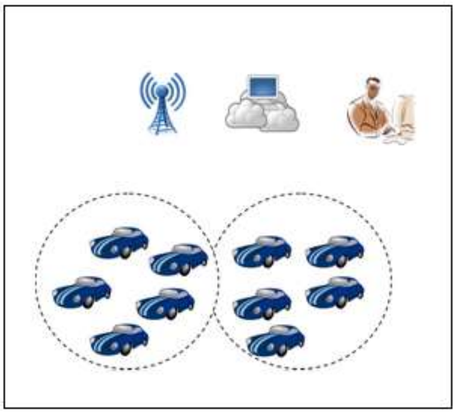

Fig 1: Network Model [32]

Literature survey:

In this section we present deep survey on internet of vehicles using IOT. Because of its great capabilities of gathering real-time information, the Internet of Vehicles (IoV) plays a critical role in offering a variety of services. In most cases, collected data is sent to a centralized cloud platform with a high demand for resources for service implementation. Edge Computing (EC) is used in the Internet of Vehicles to enable real-time services for car users by deploying physical resources near road-side units. Additionally, while various efforts are made to improve the speed of EC-enabled IoV, they do not aid in making dynamic decisions based on real-time requests. Artificial Intelligence (AI) can improve the learning capacity of edge devices, allowing for more dynamic resource allocation. Although AI has been used to improve EC performance in a lot of studies, there aren't many summaries with related concepts or possibilities. To fill this need, an extensive survey [8] on the use of AI in edge service optimization in IoV is being done. To begin, the authors define the general situation and related concepts of IoV, EC, and AI. Second, they look at edge service frameworks for IoV and look at how AI can help with edge server placement and service offloading. Finally, many outstanding issues in AI-assisted edge service optimization are investigated. In [9], Kwang and Yin focus on collaborations among various edge computing anchors and propose CVEC, a novel collaborative vehicular edge computing system. By working horizontally and vertically, CVEC may provide more scalable vehicular services and applications. Authors talk about the CVEC's architecture, concept, methods, specific circumstances, and potential technology enablers. Finally, various research obstacles are discussed, as well as prospective research prospects.

Deep Reinforcement Learning (DRL) is a new approach for dealing with problems involving time-varying features. In this work, we employ DRL to provide an efficient vehicle edge caching and content delivery strategy for minimizing content delivery latency. Y Y Dai[10] presents a multi-access edge caching and content delivery system for vehicle networks. After that, the problem of vehicle edge caching and content delivery is articulated, and a novel DRL approach is presented to handle it. When compared to two benchmark solutions, numerical findings demonstrate that the proposed DRL-based strategy is more successful. The Internet of Vehicles (IoV) has struggled to manage computationally expensive and delay-sensitive computing operations due to the proliferation of mobile devices and a plethora of complex application services. Application work is offloaded from a mobile device to a distant cloud or a local mobile edge cloud for processing to dramatically reduce latency and energy consumption. In contrast to distant clouds, mobile edge clouds are located near the network's edge. As a consequence, mobile edge computing (MEC) maximizes the usage of idle processing and storage resources at the network's edge while simultaneously minimizing network transmission latency. Furthermore, mobile devices are getting more sophisticated. The vehicle Internet is evolving into the intelligent vehicle Internet to meet the needs of mobile users in terms of service experience and quality. Artificial intelligence (AI) techs can adapt to rapidly changing dynamic situations to meet a variety of resource allocation, computing work programming, & vehicle trajectory prediction needs. Computing & storage resources are distributed at the network's edge based on this model, which is paired with MEC & AI technologies to enable real-time data processing & more efficient and intelligent services. This article examines the architecture and implementation technologies for IoV from three perspectives, namely MEC, AI, and the benefits of merging the two. The use of MEC and AI in IoV is examined and compared to existing techniques. Finally, a number of intriguing future directions in IoV are discussed [11].

In a mobile edge caching network, the authors [12] offer two innovative proactive cooperative caching techniques that leverage deep learning (DL) to forecast users' content demand. The first option involves a content server (CS) collecting data from all mobile edge nodes (MENs) in the network and then using the recommended DL algorithm to anticipate content demand across the whole network. However, because MENs are required to share the data of their local users with the CS, such a centralized system may divulge private information. As a consequence, the second technique proposes a novel distributed deep learning (DDL)-based framework. The DDL enables MENs in the network to collaborate and share information in order to decrease content demand forecast inaccuracy while protecting mobile users' personal information. According to simulation data, the recommended techniques for improving accuracy by decreasing the root mean squared error (RMSE) by up to 33.7 % service latency by 47.4 % when compared to previous machine learning methods.

The authors of this paper [13] explore the challenges of ensuring dependable computation and data storage in a geodistributed edge cloud system constructed with commodity resources. A concept called dependability factor is presented, which specifies how trustworthy a node is. Authors use this dependability factor to assign jobs to a collection of nodes in order to achieve a specific level of reliability and dynamically replicate data in order to achieve timeliness in computing and high data availability in data storage, respectively. The proposed solutions are tested on the Nebula edge cloud, and it is discovered that including the dependability factor improves performance and storage usage.

The authors [14] recommend that in a multiuser multiserver VEC (vehicular edge computing) system, load balancing and offloading be integrated, as well as allocation of resources. To maximize system utility, we first define the combined load balancing & offloading problem as a mixed integer nonlinear programming problem. When modeling the system utility, we pay special attention to the IEEE 802.11p protocol. After decoupling the issue into two sub problems, a low-complexity method is designed to jointly pick VEC servers while optimizing offloading ratio and computation resource. Numerical findings demonstrate that the proposed method converges rapidly and that our combined optimal VEC server selection and offloading strategy beats the benchmark solutions.

Multiple traffic services are supported by the Internet of Vehicles (IoV), which processes a large amount of data from sensors and video surveillance equipment. Because of the convenient resource availability for video storage and processing, video surveillance services may undoubtedly be improved with edge computing. In general, deploying a small number of edge nodes combined with surveillance devices is a common way to save money on hardware and maintenance. However, such an border node arrangement results in unreliable service distribution & complex data transfer between surveillance devices and edge nodes, lowering the surveillance service quality. Furthermore, the service's reliability is questioned since personal information may be divulged to some level during data transmission. To address these difficulties, a trust-aware task offloading mechanism (TOM) for video surveillance in edge computing enabled IoV is proposed, with the purpose of decreasing service response time, balancing edge node load, and providing privacy protection. SPEA2 (raising the strength of the Pareto evolutionary algorithm) is utilized to produce balanced task offloading solutions. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) & MCDM (Multiple Criteria Decision Making) are then used to detect the best response. Finally, the experimental simulation demonstrates that TOM is both dependable and efficient [15].

In [16], the network architecture is organized into four areas in: vehicle, infrastructure, Adhoc, and services. The applications and services are then classified in accordance with QoS criteria for safety and non-safety applications. All methods and standards have been assessed, and difficulties have been removed based on vehicular environment needs. The authors of [17] present an overview of several forms of attacks in IoV and VANET. They divide assaults into active and passive types and employ the OSI layer model for network cluster attacks. Attacks on applications as well as data are also divided into categories. In systems, however, there are no methods to detect attackers, preventing attacks, or responding to them. In [18] IoT data transmission, security is examined at the top layer. In this paper, several strategies for providing trust and security for user authentication and privacy problems are examined. There is no unified technique for dealing with security concerns at different layers. These papers focus on unique applications and services within a field.

Some papers have enhanced the environmental criteria of VANETs based on safety standards in vehicle networks. In [19], authors are researching Vehicular Social Networks (VSN). VSN enables smart mobility by utilizing the Internet of Vehicles and social media to reduce traffic congestion and prevent road accidents. Vehicles connect with each other using multiple protocols at the bottom level of the VSN architecture. User data is acquired from vehicle location and social information (such as traffic statistics) for services and apps. It provides a variety of products to people and has a strong emphasis on human elements, which are critical for vehicular connection. Scenarios and applications in these networks are centered on safety criteria and traffic anomaly detection. VSN provides data-driven applications as well as location services. Because of the restricted resources and bandwidth available in these networks, message reliability is critical. There is no priority for message delivery, and user data and social data collecting and transmission are both unresolved issues in terms of security and trust communication. To address this issue, information technology and social networking approaches should be expanded based on vehicular network features.

In [20],[19],[21], and [22], The communication and network layers have been addressed by the authors. They haven't taken into account the subsequent layers. In this article, we explore the underlying layers and basic aspects of the system based on the requirements of services and applications, following a broad assessment of systems through designs. We have a taxonomy categorization in general and according to all levels of architecture. In [23] vehicle sensor networks, protocols and applications are investigated. Security checks and security risks are evaluated on a separate layer. Security issues, nonfunctional needs, and trade-offs are handled when considering a collection of protocols and applications. However, no information on evaluation measures is available. Such data can be utilized as a starting point for developing intelligent transportation systems. It also gives a broad overview of vehicular network architecture and deployment. In our paper, we attempted to classify the studies based on their implementation and simulation methods. Several uses in the network of linked automobiles have been proposed. A number of researches on application classifications and design techniques are presented, including: [24] presents a basic classification of traffic management service applications, as well as framework, communication, and nonfunctional aspects. In cloud architecture, a hierarchy for VANET was developed. This taxonomy investigates vehicle clouds and cloud environments for vehicular networks. However, this taxonomy is technology dependent and cannot be extended to a universal classification of applications. Some research has been done on application architecture in general. In [25], many services & applications are analyzed from three perspectives: environment, systems, and applications. These applications are related to safety, traffic control, and entertainment. They present a set of criteria for assessing performance.

Table 1: Studies related to IoV

Review type	Category	Main topic
Survey [23]	Communication and networks	Protocols and applications
Systematic Review [26]	Communication and networks	Taxonomy for routing protocols
Survey [27]	Application and Services	Transport application
Survey [20]	Architectures	V2X communications
Survey [28]	Architectures	Architectures based on services provisioning on the cloud environment
Survey [29]	Communication and networks	Vehicular ad-hoc network
Survey [30]	Communication and networks	Communication protocols and standards
Survey [19]	Communication and networks	Vehicular networks
Survey [31]	Architectures	Architecture review
Survey [22]	Communication and networks	Vehicular Named Data Networking

Survey [18]	Application and Services	Security and communications in services
Survey [25]	Application and Services	Context-aware applications

Conclusion:

A basic taxonomy is derived in this review. The architectures made available for IoV are examined. The classification evaluated quality parameters in the majority of architectures, services, as well as applications introduced and categorized at the highest level. In domain-specific applications, the most major factors are response reliability as well as accuracy. In future studies, qualitative parameters, environmental resource management, & appropriate frameworks for execution should be enhanced

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