IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

SPECIAL SECTION ON SUSTAINABLE INFRASTRUCTURES, PROTOCOLS, AND RESEARCH CHALLENGES FOR FOG COMPUTING

Received September 9, 2018, accepted October 4, 2018, date of publication October 10, 2018, date of current version October 29, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2874592

Context-Aware Data-Driven Intelligent Framework for Fog Infrastructures in Internet of Vehicles

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This work was supported in part by the Research and Graduate Studies Office & OpenUAE Research and Development Group, University of Sharjah, and in part by the Dubai Electronic Security Center, a governmental entity in the UAE.

ABSTRACT Internet of Vehicles (IoV) is the evolution of vehicular ad-hoc networks and intelligent transportation systems focused on reaping the benefits of data generated by various sensors within these networks. The IoV is further empowered by a centralized cloud and distributed fog-based infrastructure. The myriad amounts of data generated by the vehicles and the environment have the potential to enable diverse services. These services can benefit from both variety and velocity of the generated data. This paper focuses on the data at the edge nodes to enable fog-based services that can be consumed by various IoV safety and non-safety applications. This paper emphasizes the challenges involved in offering the context-aware services in an IoV environment. In order to overcome these challenges, this paper proposes a data analytics framework for fog infrastructures at the fog layer of traditional IoV architecture that offers context-aware real time, near real-time and batch services at the edge of a network. Finally, the appropriateness of the proposed framework is verified through different use cases in the IoV environment.

INDEX TERMS Context-aware computing, data driven intelligence, fog computing, Internet of Vehicles.

I. INTRODUCTION

Efficient Transportation systems are essential to increase the productivity of a nation. The estimations show that population's time spent on the roads is increasing [1]. This dependency on the transportation systems, however, poses several challenges. First of all, the congestion is surging because of the increasing number of vehicles on the road. The congestion is a key source of air pollution in metropolitans around the world due to increases in the fuel consumption. Furthermore, the congestion poses many safety issues such as risk of accidents. The performance of transportation systems plays a key role in the economic strength of a country, so effective technologies are required to address the inherent challenges.

VANETs have seen significant advancements in recent years. IoV is the latest development for VANETs that enables each entity of the network to be connected to the Internet for sharing information with other entities. IoV endorses strong interaction between vehicles, infrastructure and humans by empowering them with connectivity, computing and processing capabilities through Vehicle to Vehicle (V2V), Vehicle to Infrastructure (V2I), Vehicle to Sensor (V2S), Vehicle to Human (V2H), Vehicle to Device (V2D) and Infrastructure to Infrastructure (I2I) [2]. With technological advancements, IoV is expected to provide vehicles, drivers and passengers with unprecedented safety and convenience such as, accident warnings, vacant car parking notifications, restaurants' discount vouchers, dangerous road warnings, emergency vehicle caveats, internet and multimedia sharing, traffic light management and road safety messages etc.

There are different technologies used to provide the required infrastructure to collect, process, and analyze the generated data to enable data-driven intelligence. Vehicular Cloud computing (VCC) has empowered the ITS systems to enable range of different applications from safety to traffic management [3]. This paradigm requires all the sensed data from vehicles and environments to be sent towards

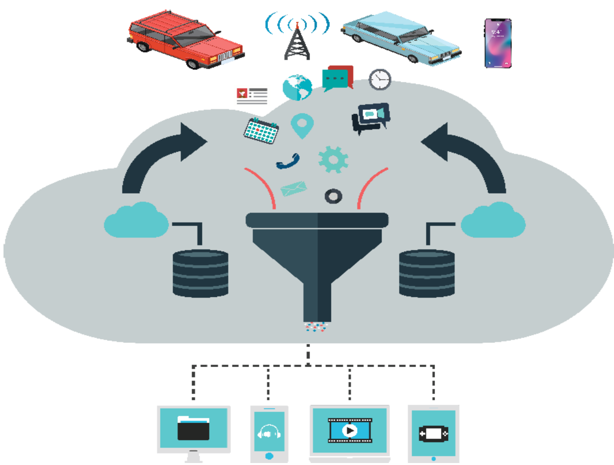

FIGURE 1. Data-driven intelligence system.

a centralized cloud. The integration of cloud computing with ITS provides the required infrastructure to store, process and analyze mammoth amounts of data. VCC also orchestrates various services for different applications such as traffic congestion management and traffic predictions. These applications are required to interact with a centralized cloud to consume offered services. This paradigm offers a great platform for offering services based on long-term data. However, this centralized paradigm struggles to deal with delay-sensitive applications such as Traffic Light Management, Vehicle Tracking, Road Safety Messages, Accident Warnings, Emergency Vehicle Warning, Commercial Advertisement, Alternate Routes, etc. On the other hand, Fog computing offers a distributed cloud model to enable the delay-sensitive applications. In this paradigm, all the sensed data is gathered by the designated fog servers in the vicinity of the vehicles and the environment [4]. To reduce delay and increase energy efficiency, the data should travel just one hop before it can be processed and analyzed. All the fog servers in different areas orchestrate their own services to enable range of delay-sensitive applications. Figure 1 shows a data-driven intelligence system in action that collects data and analyzes it to produce useful analytics for different applications of IoV.

In IoV, context awareness plays a vital role. An important aspect in IoV is to capacitate entities to be conscious about the conditions around them, especially those that are highly pertinent to them. The context is multifarious and depends on various attributes such as applications, preferences and social relationships of the vehicle's owner, vehicle's model, time, location, and sensor data etc. The applications of IoV out of context can be highly inconvenient for the entities of IoV system. For example, providing speed limit information of highways to the vehicles inside the city might be highly out of context. Similarly, providing information of vacant car parking in a mall to vehicles in a hospital parking will be out of context and might cause inconvenience to the drivers.

Several efforts have been done to provide a data-driven intelligence framework for IoT that are mainly based on centralized cloud, however, not much has been done for IoV system and hence, this article is expected to fill the gap in literature through following contributions:

- Emphasize the challenges involved in offering context-aware services in an IoV environment.
- Propose a context-aware data intelligent framework for fog infrastructure by extending the fog layer of the traditional IoV architecture to enable delay-sensitive IoV applications.
- Highlight the appropriateness of the proposed framework through real life use cases.

This article is organized in the following way. Section II discusses the related efforts that address the similar issues. The Traditional IoV architecture is explained in Section III and its challenges are highlighted in Section IV. The detail of the proposed data-driven intelligent framework is covered in Section V. The related use cases are presented in Section VI. Finally, the paper is concluded in Section VII.

II. RELATED WORK

IoV is an emerging field that has been embraced by several researchers from academia and industry. Data driven intelligence is of utmost importance to utilize true potential of IoV in safety and non-safety applications. In order to ensure efficiency, reliability and dependability on IoV systems, context-aware data is paramount that is evident from review of literature on VANETs. This section provides summary of literature review on context-aware applications, services, architecture along with challenges and proposed solutions of vehicular networks.

In literature, the provision of data-driven intelligent vehicular applications is addressed by different research efforts. Data-Driven Intelligent Transportation System (D2ITS) that utilizes the data collected from various sources is proposed in literature [5] as an evolution of the traditional Intelligent Transportation Systems (ITS). The components of D2ITS include advanced public and urban transportation systems, vehicle control and management systems, and traveler information systems. Furthermore, the D2ITS is categorized in to Vision-Driven ITS, Multisource-Driven ITS, and Learning-Driven ITS. Vision-Driven ITS is based on the data generated by on-vehicle object detection sensors and applicable in different autonomous vehicle applications. Multisource-Driven ITS utilizes data generated from multiple sources such as GPS, and Laser radar to enable different applications such as traffic warning system. Learning-Driven ITS uses both real-time and historical data to predict future events. This form of ITS employs different learning mechanisms to effectively forecast future warnings. Another effort [6] presented a comprehensive review of data management perspective in Vehicular networks. The data management tasks and related challenges in vehicular networks are identified in this paper. Furthermore, the paper covered the details about context, data relevance calculation, data dissemination and aggregation, and query processing. These papers emphasize the potential of data-driven intelligence and related issues in vehicular networks, but the latest trends such as cloud, fog and IoV are not taken in to account.

There are many efforts that discuss the role of data intelligence generally in IoT environments. Ahmed *et al.* [7] reviewed the role of big data analytics for IoT systems. They also have covered the detail of recent advances in big data analytics and related platforms and solutions. The general requirements of IoT environments and open research challenges to enable data-driven intelligence are also presented by the authors. Furthermore, few IoT applications, along with Smart transportation, are assessed by the authors to highlight the potential benefits of big data analytics. Similarly, Qin *et al.* [8] presented a data-centric perspective of IoT. They have reviewed recent techniques for data stream processing, storage models, event processing and searching in IoT. However, these papers only provide reviews of the potential of big data analytics in IoT but do not provide a framework to avail the benefits. A data-centric framework is proposed in [9] to support the development of cloud-based IoT applications. The framework is composed of three components: Data Source Manager, Cloud Manager and Application Manager. Data Source manager interact with multiple data sources and provides the interface for applications. Cloud Manager is responsible for the provision of resources based on the applications' requirements and monitoring of the cloud's performance. Finally, Application Manager facilitates users to execute their applications in the cloud. These papers, however, only either address the general IoT requirements or mostly focused on centralized cloud-based solutions and are not focused on IoV scenarios.

VCC based efforts focused on enabling data-driven intelligence based on vehicular data gathered at a centralized cloud. Sookhak *et al.* [3] have reviewed the current Cloud Computing technologies and discussed the taxonomy of vehicular networking. They have also analyzed the technologies in the context of VCC. Moreover, authors presented general architecture, security and key management issues, and potential vehicular applications. Their paper also highlighted the open research issues such as context-based routing mobility and unstable communication links. A IoT based Vehicular Data Cloud architecture is proposed in [10] to provide on-demand services to customers through vehicular cloud. The layered architecture integrates various information and communication services made available to users using Service-Oriented architecture (SOA) based cloud services. SOA also abstracts the implementation details by integrating various middleware systems. Furthermore, it is argued that these SOA-based services ease the process of creating new application for developers by organizing, aggregating and packaging different business application services. The paper also highlighted the related future challenges and opportunities. These papers partially address the IoV requirements, because the papers have only focused on the data-driven intelligence at a centralized cloud server.

There are few efforts that cover distributed data-driven intelligence in IoT environments. Fog Computing [11] paradigm aims to create large distributed cloud-based services by deploying fog nodes at the edge of various networks. The fog nodes are allowed to have different configurations and capabilities [12]. Applying Fog Computing paradigm in IoT has several benefits such as reduced latency, efficiency and agility [13]. Bonomi *et al.* [14] have examined the potential of fog-based big data analysis to enable disruptive business models. The authors discussed few IoT use-cases to illustrate the requirements of fog computing. Furthermore, they proposed a high-level software architecture, to realize different applications, that has three layers: Abstraction layer, Service Orchestration layer, and Application layer. The Abstraction Layer integrates the heterogeneous IoT devices by providing an abstraction API. Then, the Orchestration layer contains a Foglet that acts as a resource manager, a distributed storage for policies and other data, and a messaging bus to deliver messages for resource management and service orchestration. Finally, the Application layer provides Data and Control APIs to enable applications to utilize the distributed data store and define the deployment configurations. Another effort [15] discussed a general architecture for the provision of consumer centric IoT services. These papers cover the fog based data-driven intelligence, but the IoV requirements are only partially addressed.

Fog computing paradigm is also applied to vehicular network in few articles. The case study of connected vehicles is briefly explored to highlight how fog-based semantic data analytics can offer services for the discovery and management of the vehicles. The term Vehicular Fog Computing is coined in [16] by considering vehicles as fog nodes. Different application scenarios are considered such as moving and parked vehicles as infrastructure units of the fog paradigm. However, the paper also emphasized different open challenges to be tackled before some useful applications can be realized. Zhang *et al.* [17] considered offloading computation to local fog servers to reduce latency and increase scalability. The authors also proposed a regional cooperative fog-computing-based intelligent vehicular network (CFC-IoV) to manage the big data generated by IoV in a smart city environment. Another approach [18] has proposed a new fog-based VANET architecture by following the Software Defined Networking (SDN) paradigm in order to offer preprocessed services at a low latency. Another similar effort [4] considers vehicles as IoT resources, but briefly mentioned the data related layer. A Pub/Sub-based fog computing architecture is also proposed for IoV in [19]. Another survey paper [20] reviewed the role of fog computing in IoV and proposed an abstract architecture based on the lambda architecture [21]. This architecture is further augmented with domain-based semantic ontology. These efforts are more focused on general architecture to realize fog computing and have not addressed the data-centric perspective in detail to enable intelligence.

Context-awareness and Content Centric Networking (CCN) has been studied in context of VANETs by different authors. Wan *et al.* [22] proposed a multi-layer context-aware architecture for vehicular networks with mobile cloud support. The authors have divided the applications and services of context-aware cyber-physical systems into three computational layers; vehicle, location and cloud. In vehicular computational layer, vehicle is expected to provide data about vehicle sensors, environment, driver and passengers. In location computational layer, Road Side Equipment (RSE) can exchange context-aware information with On-Board Equipment (OBE) of vehicles. Context-aware information exchange between RSE and vehicles can help in generating real time information, e.g., traffic information. Besides proposing an architecture, authors analyzed two service components, e.g., vehicular social networks and context-aware vehicular security. Finally, a context-aware application scenario of dynamic car parking services has been exemplified to evaluate the proposed architecture. Due to high mobility in VANETs, context-awareness plays a vital role for content generation and consumption. Duarte *et al.* [23] have analyzed the efficiency of approaches combining CCN, Floating Content (FC) and Software Defined Networking (SDN) for adaptive VANET architecture to assimilate periodic connectivity, varying node density and mobility patterns in ensuring high QoS. The major contribution of this article is to highlight the potential of SDN in VANETs to ensure optimized content dissemination in a network, by analyzing the factors that affect CCN and FC based content dissemination and investigation of reduction in content retrieval time by utilizing technologies like Wi-Fi and LTE in vehicles.

Context and social relationship management in VANETs have been explored by some researchers. Nassar *et al.* [24] have provided an overview of context-aware processing and communication gateway associated with VANETs. A context-aware system architecture for VANETs has been discussed along with the challenges involved in knowledge querying and information dissemination in VANETs. A context-aware VANET system is layered into smart dissemination, context processing and context collection and modelling layers. Finally, smart dissemination is used as a mechanism to disseminate relevant information to the nodes. The factors that help in choosing the appropriate communication include, type of service and relevance of the service to nodes' context. Similarly, Shin and Byun [25] have proposed a Social Enabler (S-Enabler). In order to demonstrate its working, they applied S-Enabler to a vehicle to ensure context-aware and energy saving services. A middleware architecture for S-Enabler is designed that comprises of six management modules; context management, the cooperation management module, the social management module, the session management module, service management module and finally a knowledge repository. The authors have also proposed energy saving algorithm based on social behavior. The experiments performed to evaluate the performance of energy saving in vehicles illustrated reduction in fuel consumption by 31.7%.

Based on the literature, there has been significant work done in the domains of Big data, IoT, IoV and Fog Computing. However, there is a gap in the provision of context-aware and delay-sensitive services. This paper aims to fill this gap by proposing a framework to enable context-aware data-driven intelligence in IoV environments.

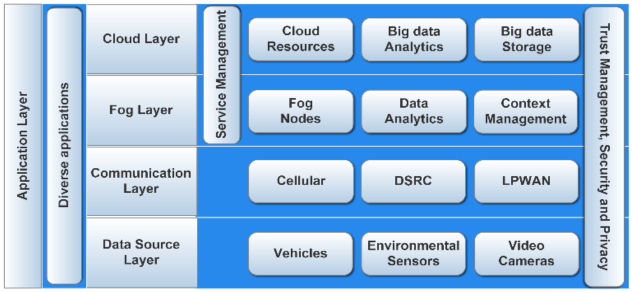

FIGURE 2. Traditional IoV architecture.

III. TRADITIONAL IOV ARCHITECTURE

IoV is an emerging field that has the potential of utilizing various state-of-the-art concepts like IoT, Big Data Analytics, Wireless Communications, Safety and non-safety application and Security etc. Recently, there have been some efforts in developing a generic IoV architecture that provides overall frame of reference for future researches in this area. A generic IoV architecture comprises of a data source layer, communication layer, fog layer, cloud layer, application and security layer [26]. A simplified version of generic IoV architecture is illustrated in Figure 2.

Each layer of the architecture is responsible for performing certain tasks. At Data Source layer, data is collected from various sensors, e.g., vehicle sensors and environmental sensors incorporated into Road Side Units (RSUs). Communication layer is responsible for data transmission between different entities of the system, e.g., vehicles, RSUs, passengers, drivers, pedestrians and cloud etc. One of the major responsibilities of Fog layer is to ensure the required scalability with the provision of fog-based decentralized architecture in a IoV network through huge amount of data generated by different entities of the network. The Cloud layer provides resources to perform complex computations, store enormous amounts of data, and a place to make system-wide decisions. Application layer is responsible for providing safety and non-safety application through V2V, V2I, V2S, V2H and V2D communication [2]. Finally, Security layer is responsible for securing the data throughout the IoV architecture.

This article is expected to explore the capabilities of the Fog layer in IoV systems to ensure offering of context-aware services in an IoV environment by proposing a framework that enables delay sensitive applications.

IV. IOV CHALLENGES

IoV system faces various challenges due to its dynamic nature and real-time data requirements. Several researches are under process to improve the overall efficiency of IoV systems. A comprehensive review of literature assisted in summarizing the following major challenges faced by IoV system for their design, development and deployment.

A. HETEROGENEITY AND INTEROPERABILITY

An IoV system involves communication between diverse entities of the system like vehicles, RSUs and drivers and passengers' handheld devices etc. Each entity of the system requires disparate communication scheme and is capable of generating distinct type of data. For example, in a V2I communication, if a vehicle can communicate through a cellular technology, e.g., 2G, 3G or 4G etc. and a RSU can only communicate through Dedicated Short Range Communication (DSRC); the communication might never occur due to unsupported communicating technologies [27]. Similarly, in a V2V communication, vehicles supporting DSRC might still not be able to communicate with each other if data sent by one vehicle is unrecognizable by another vehicle due to different encryption techniques used by the manufacturers of the vehicles. Due to scalable and dynamic nature of IoV, the network is expected to grow significantly with discrete nodes that might be different from each other in communication protocols, security algorithms, data sharing mechanisms and other supporting technologies. Hence a mechanism is required that enables heterogeneous entities to socialize with each other.

B. REAL TIME DATA

One of the major requirements of IoV system is dissemination and gathering of real time data to and from its distinct entities. In some cases, processing of the data before dissemination and gathering requires real time analysis to ensure appropriate actions [28]. For example, an ambulance carrying a patient in critical condition to the hospital would require real time information of the traffic to avoid jams and congestions to ensure timely delivery of patient to the hospital. A slight miscalculation in data delivery of traffic information in this case might result in ambulance being stuck in a traffic jam that would end up in compromising the life of the patient. In IoV, mostly safety and non-safety applications need data analysis in the cloud that depends upon many factors like available bandwidth, cloud processing, computing and storage capabilities, complexity of encryption algorithm and amount of data etc. An IoV system requires an efficient technique that ensures real time data delivery to enable delay sensitive applications.

C. CONTEXT-AWARENESS

A vital feature in IoV is to empower vehicles to be context-aware, e.g., to be cognizant of their surroundings particularly the ones that are of high relevance. Context-awareness in IoV starts with gathering data through in-vehicle or environmental sensors, converting this sensing information in to high level contextual information and finally taking an action based on this contextual information. For example, in a smart vehicle, a camera installed above the driver seat might constantly monitor the driver to measure the fatigue level through algorithms that use driver face expressions to calculate driver fatigue. This information from the camera (sensing component) is then converted in to high level contextual information by gathering other information like vehicle speed, road type, vehicle movement and inter-vehicle distance to finally alarm the driver of the situation or suggesting the driver to take a break. Context-awareness in IoV is extremely useful as it can assist drivers in understanding their own driving behavior, improve fuel efficiency by providing less-traffic routes, enables authorities in managing parking slots and govern traffic rules in highly populated urban areas [29]. An IoV system entails systematic context-awareness process that ensures effective decision making for autonomous entities.

D. QUALITY OF SERVICE (QoS)

IoV enables plethora of applications based on V2S, V2V and V2I communication. These applications have diverse QoS requirements in terms of latency, throughput and jitter, etc. The provision of required QoS depends on many factors such as vehicle's speed, density of vehicles in the vicinity, application's data requirements, location of sources, characteristics of the communication technologies involved, and the processing requirements [2]. For example, it is easy to meet real-time requirements of an application that only requires data from a sensor with peer to peer (P2P) connection in a vehicle. However, it is quite challenging to provide QoS to an application that require data from a source that is located multiple hops away. Moreover, the heterogeneity of the involved communication technologies further augments the issue of meeting QoS requirements. The provision of QoS becomes extremely challenging in case of IoV applications with high QoS requirements, for example, some applications demand low latency, but require video data to be processed from multiple sources. All these challenges make the provision of QoS a daunting task in IoVs. A data driven intelligent framework needs to consider these diverse QoS requirements of various applications to aid those applications to run efficiently and effectively.

E. DATA QUALITY

IoV data-centric applications assume that the quality of data will be up to some acceptable level, so the efficacy can be guaranteed. The data generated in IoV is prone to errors due to multifarious reasons such as data source issue, unreliable communication link, noise, etc. The data source can malfunction due to technical reason that can result in inaccurate data. These data can severely impact the outcome of an application and increase the possibility of serious incidents in the context of safety applications [27]. The heterogeneity of communication technologies can negatively impact the end-to-end reliability of the data and needs to be taken in to account by a IoV data centric framework. To tackle with noise related issues there are several solutions available in the literature that analyze the data to detect and eliminate different types of noise. An intelligent IoV framework may decide to offer a best-effort approach by reducing the number of dimensions depending on the context and QoS requirement of an application.

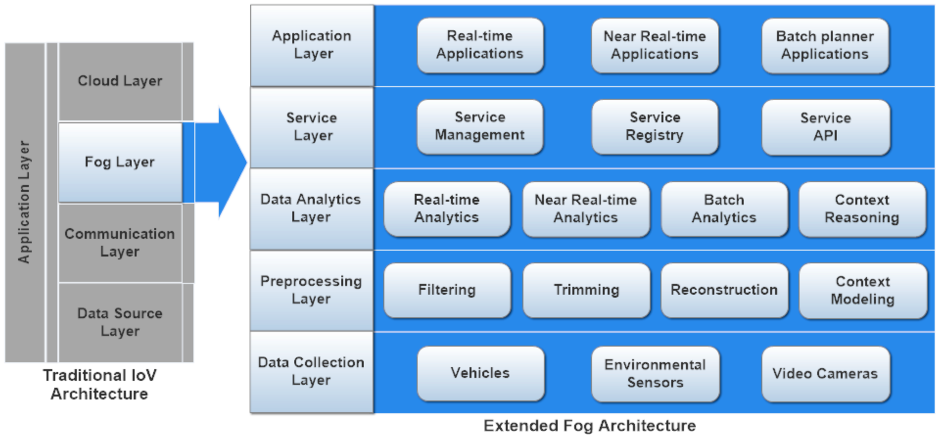

FIGURE 3. Proposed data-driven-intelligent framework.

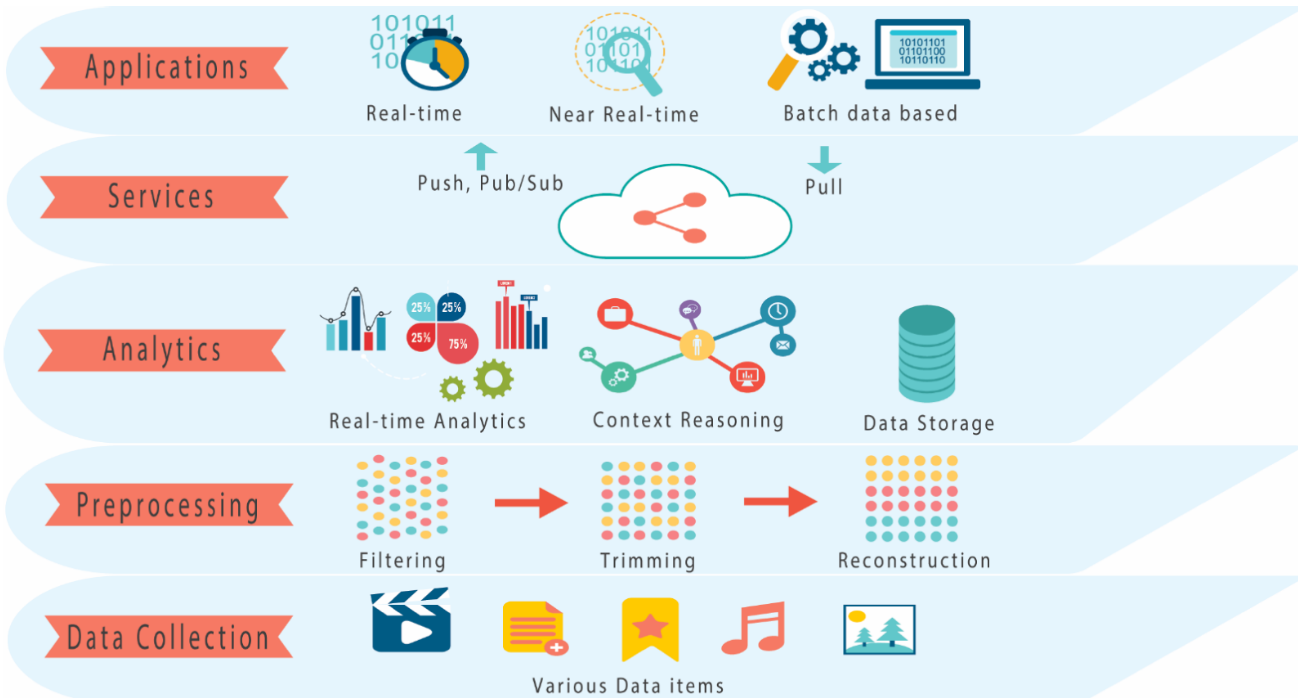

FIGURE 4. Holistic view of proposed data-driven-intelligent framework.

V. PROPOSED DATA DRIVEN INTELLIGENT FRAMEWORK

IoV networks are highly scalable with nodes capable of dynamically changing network topologies. However, IoV poses unique set of challenges for designing a data analytical framework due to its peculiar characteristics. Fast moving vehicles require brisk computation and processing of information without any delay to avoid miscommunication that can cause serious inconvenience on the road to not only the entity requesting the information but to other entities related to it. As the entities in IoV are highly dynamic in nature, the context of the information is of utmost importance as a slight change in the context might result in providing inappropriate information to the vehicles on road.

Figure 3 illustrates proposed data-driven-intelligent framework for providing context-aware applications and services for IoV. The proposed framework is an extension of Fog layer of the traditional IoV architecture presented in Figure 2. This section provides the details of responsibilities of each layer of the architecture. Furthermore, Figure 4 provides a holistic view of the proposed data-driven intelligent framework for a better understanding of the working of each layer of the framework.

A. DATA COLLECTION LAYER

This layer deals with the collection of data at the fog layer of the IoV system, e.g., RSUs that can provide computation,

TABLE 1. Protocols at physical world layer.

Data Source(s)	Technology	Protocol	Type	Description
Vehicle Sensors	V2I / V2S	CIP	Control and Information Protocol	Collects data from vehicle sensors
Vehicle Controller	Intra-Vehicle	CAN	Communication protocol	Assists in communication between Vehicle sensors and On-Board Unit (OBU)
Environmental Sensors	V2I / I2I	I2C	Connection protocol	Contributes in interfacing various RSU modules
Handheld Devices	I2P / V2P	TCP/IP	Communication protocol	Helps in collecting data to and from handheld devices
Cloud	I2C (Infrastructure to Cloud)	TCP/IP	Communication protocol	Supports in fetching data to and from cloud

processing, storage and networking services. In IoV systems, the data can be collected from distinct sources like vehicles, road sensors and handheld devices of drivers, passengers and pedestrians. Besides data collected from the sensors, this layer is also responsible for collecting data from other peer sources like neighboring RSUs and if required from cloud as well. The type of data collected from other sources can be driver profile, vehicle details, traffic information, weather data, empty parking slots and alternate routes etc. The context acquisition process at this stage evaluates context information from collected data based on the source, sensor types and their responsibilities. In the proposed framework illustrated in Figure 3, the data is expected to be collected by a fog node e.g., RSU and is kept till further processing. Furthermore, the proposed framework requires the fog nodes to collect data based on the context.

Fog based distributed information collection proposed by the framework helps in reducing the burden on each fog node and eventually the entire system [17]. Each fog node is responsible for updating the collected data dynamically. The information from fog nods can be combined to provide contextual information to the entities of the system. It is worth noting here that Data Collection layer at Fog units is not like Data Source layer of a typical IoV architecture. The major difference between the two is that Data Source layer of IoV architecture is responsible for physicality of the sources like vehicle and environmental sensors, however, the Data Collection layer is more of a container of the data acquired from various sources like sensors, handheld device and at times from cloud as well.

The data driven intelligence based on the context provided by the proposed framework helps the system in smartly collecting the data from various sources that ensures less burden and provides better efficiency to the entire IoV system. Data is collected from various sources through different protocols at Data Collection layer of Fog as illustrated in Table 1.

B. PRE-PROCESSING LAYER

This layer of the architecture is responsible for data filtering (extraction), trimming, reconstruction and modeling. In the proposed data-driven intelligent framework, this layer is considered extremely important as it collects the raw data from the data collection layer and gives it a specific direction for above layers to analyze and convert the data into meaningful information [30]. Below are the details of the features provided by this layer:

1) FILTERING (EXTRACTION)

One of the major responsibilities of the pre-processing layer is to filter the data from enormous amount of data collected from various sources in data collection layer [31]. In IoVs, entities are feeding the system with data that can serve the purpose for diverse types of safety and non-safety applications. The filtering component of the pre-processing layer ensures that relevant data is extracted based on the application or service requesting the data from the system. Filtering or extraction of data from large chunk of collected data eases the process of analysis, storage and communication by providing only relevant data for specific applications and services.

2) TRIMMING

In pre-processing layer, it is of utmost importance to trim the unnecessary information from the collected data to avoid redundant utilization of resources at fog units due to their limited computing, processing, storage and communication capabilities [32]. The trimming component of pre-processing layer ensures circumvention of duplicate, incomplete and faulty data. Duplicated data is merged to get the most recent information; incomplete and faulty data is requested again to avoid inaccuracy of information. Trimming serves as a successor to the filtering component of the pre-processing layer as it will trim only the filtered or extracted data relevant to requested application.

3) RECONSTRUCTION

In order for the analytical layer of the framework to analyze the data, it should be complete, clean, error-free and contextual in nature. The reconstruction module of the pre-processing layer ensures the accurate information for analytical layer by reconstructing the trimmed data in an analytical layer readable manner. This module also assists in segregating the actual required data, metadata and any additional information required by the actual data.

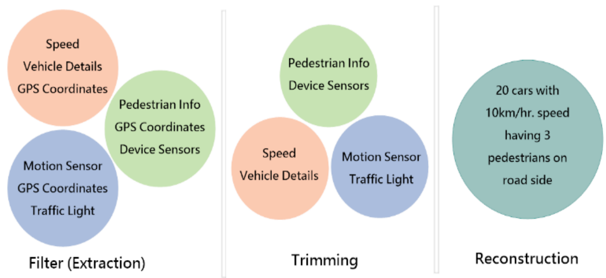

FIGURE 5. Pre-processing layer role based on IoV scenario.

TABLE 2. Features of data pre-processing layer.

Features	Responsibility	Data Collection Entities
Filtering	Filtration and Extraction of Data	All participating entities of IoV
Trimming	Error Detection Error Correction Duplication Removal Data Completion	Selected entities of IoV
Reconstruction	Data Segregation	Selected entities of IoV

The context information is modelled to understand its details such as properties of IoV entities and their mutual relationships. The modeling of context information is done using different modeling methods such as key-value pairs, objects, graphical objects, ontology based, and hybrid context modeling. The Key-value pair scheme is the simplest form of modeling that is flexible and easy to understand, however, it's not suitable to explain complex structures with relationships. The object based scheme uses object oriented principles to classify context in classes and define relationships between the vehicular entities. This scheme requires specification for validation and can increase complexity of the reasoning stage. The graphical object scheme takes one step further and uses XML to explain different objects of IoV system. A semantic ontology of context is created by ontology based modeling to represent it using semantic ontology languages such as Resource Description Framework (RDF) and Web Ontology Language (OWL) [33]. This modeling technique is more sophisticated and used by databases and semantic web to provide required interoperability to IoV system. However, its complexity can be hurdle in its employment on a constrained fog node. The hybrid modeling uses multiple modeling scheme to ripe the advantages of each modeling technique. A fog node of IoV selects a modeling scheme based on its capabilities.

The aim of the pre-processing layer is to make the raw data collected from data collection layer useful for above layers. In IoV, due to highly dynamic nature of the system, analysis of data is expected to be done in a swift and efficient manner and hence filtering, trimming and reconstruction of data is paramount. Figure 5 illustrates a scenario that further highlights the role of pre-processing layer in IoV systems.

Fog nodes in IoV collect massive amount of data from vehicles, pedestrians, drivers, passengers and neighboring fog nodes. However, not all applications require all the collected data and hence pre-processing layer plays a vital role in filtering the data. If analytical layer requires traffic info in an area based on the request of the application, the pre-processing layer will provide the required information to the analytical layer by filtering, trimming and reconstructing the required data. For example, the extraction module extracts vehicle speed and vehicle details, GPS coordinates from vehicles; motion sensors' readings, GPS coordinates, traffic light status from RSU; pedestrian info, GPS coordinates and handheld sensor readings from pedestrian devices excluding all the other unnecessary data from the participating entities. The extracted data is then trimmed to remove any duplication or errors from the extracted data. In this scenario as illustrated in Figure 5, GPS coordinates are appearing repeatedly and hence trimmed from the data. The trimmed data is then handed over to the reconstruction module that restructures and models the data in way understandable by the above layers. In this case, the reconstruction module provides a description of the traffic info to the analytical layer based on the request from an application. Table 2 presents the features of pre-processing layer of the framework with respective data collection entities.

C. ANALYTICS LAYER

This layer fulfills the main aim of fog-based system to bring the data intelligence at the edge of a network. This intelligence is realized by analytics and can support both delay-sensitive and delay-tolerant applications at the intermediate nodes. The data received at this layer is collected and preprocessed by other layers and made ready to be analyzed. Moreover, the current context information is also received at this layer. Based on general lamda architecture [20], we assume three levels of data analytics to be performed at this layer: Real time analytics, Near real time analytics and Batch analytics. The capabilities of a fog node determine whether it can support all kind of analytics.

1) REAL-TIME ANALYTICS

The real-time analytics is essential for fog nodes. Each fog node is required to support some form of real-time analytics. Real-time analytics aids application that are delay sensitive and require the necessary complex processing to be done within certain amount of time. There are many IoV applications that demand such a QoS such as safety applications. For example, a fog node may assist an autonomous car to perform complex video processing from the surrounding cameras to know whether a pedestrian is about to appear from a street. Real-time analytics are performed on elements of a data stream that need to be processed in real-time to get useful information from it. The real-time processing is limited by the constraints such as available main memory to run an in-memory algorithm. Therefore, these constraints

TABLE 3. Algorithms for real-time analytics.

Category	Algorithms	Sample Outcome	Application
Counters	Cardinality counter	Total number of entities such vehicles.	Traffic management
	Inversions counter	Whether the received vehicle data is sorted	Safety application
Basic Estimators	Quantiles estimator	Aggregative quantile of heavy vehicle in vicinity	Route planner
	Moments estimator	How many pedestrians are passing	Pedestrian crossing light planner
Pattern detection	Anomaly detector	Vehicle shared data has irregularities	Rouge node detection
	Pattern matcher	Pattern of traffic congestion	Congestion management
	Subsequences detector	Unsafe driver on the road	Safety application
Graph Analysis	Path locator	Path between two vehicles	Live Traffic
	Graph analyzer	Path analysis between multiple vehicles	Live traffic safety
Prediction	Clustering	Cluster data to create an image, or video shared by a vehicle	Offloading processing
	Data predictor	Predict a missing attribute in the data shared by a vehicle	Traffic signal planner
	Size predictor	Dynamic size of the graph of current vehicles	Congestion management

determine whether an approximation will be preferable using sliding windows instead of a refined solution. The real-time analytics employ different algorithms to estimate Cardinality, estimate quantiles and moments, count inversions, find subsequencing, path analysis, anomaly detection, discover temporal pattern analysis, data prediction, clustering and graph analysis. Table 3 illustrates the examples of these algorithms and relates the output to different IoV applications. The cardinality estimation algorithms such as Hyperloglog [34] are used to analyze a data set and count the unique elements in it, and some algorithms are used to estimate quantile of constrained memory node. The moments estimation algorithms [35] are used to estimate the frequency of different elements. The discovery of inversions and anomalies in a data stream is performed by algorithms such as inversion counter and Anomaly detector [36]. Some algorithms are used to discover patterns and subsequences in traffic such as Temporal Pattern detectors and subsequence evaluators. The graph analysis based algorithms analyze dynamic graph to determine useful IoV information such as determine a path between different nodes, find a vertex cover of the current traffic. The predictive real-time algorithms create clusters from a data stream, predict missing values and size of a stream.

2) NEAR REAL-TIME ANALYTICS

The near real-time analytics requires data that can span up to seconds or minutes. The applications that rely on these analytics such as Complex Event Processing (CEP) applications can tolerate delay for some time because of their data requirements. It uses the similar real-time algorithms but on historic data that is gathered from multiple sources [37]. For example, a traffic light signaling control application will require data of the number of vehicles exited and entered the road within last minute to decide when to change the traffic signal. The outcome of these analytics is more granular and gives a bigger picture of the fog vicinity compared to real-time analytics. The analyzed data is stored for a while in cache memory using Memcached and Redis, or the local database depending on the size of data before it can be discarded.

3) BATCH ANALYTICS

Only few highly capable fog nodes can perform batch analytics, because of its high processing and memory requirements. The batch analytics support applications that require historic data from hours to days about the vicinity. For example, a road-work related information may be shared with every user entering the vicinity of a fog node. Similarly, a road traffic management application can update the traffic light scheduling algorithm based on the trend of the past hour. These analytics can utilize advanced machine learning techniques such as Deep Learning and Deep Reinforcement Learning (DRL) to offer more sophisticated analysis [34]. There are many real-time Stream Processing Engines such as Apache Spark, Storm, Flink and Samza, that are developed by industry and open source communities to handle the fog-based batch analytics. The key benefits of using these platforms include provision resilient analytics even when the data is out of order or some values are missing and distribute processing across processors and fog nodes to provide required scalability. These are designed for cloud based real-time batch analytics but can work on capable fog nodes.

4) CONTEXT REASONING

The received and modeled context information is reasoned to extract useful information by all levels of analytics to enhance the analysis. To perform reasoning, the modeled context information is first of all validated to check it for missing data, and outliers. Then, context information provided by different entities is infused to get a more reliable and higher-level inference from it. At the final stage specific reasoning technique is employed that analyzes the infused information to get high-level context information [38]. There are different reasoning schemes available such as fuzzy reasoning, k-nearest neighbors, naïve bayes classifiers, probabilistic

TABLE 4. Fog-based applications and users.

<table>
<tr><th>Application</th><th>QoS requirements</th><th>Service Access strategy</th><th>Users</th></tr>
<tr><td>Adaptive Traffic management</td><td rowspan="6">Real-time</td><td rowspan="6">Push-based</td><td>Local Authorities</td></tr>
<tr><td>Live neighbourhood watch</td><td rowspan="2">Police</td></tr>
<tr><td>Live Traffic</td></tr>
<tr><td>Live traffic safety</td><td rowspan="2">Drivers</td></tr>
<tr><td>Live congestion Predictor</td></tr>
<tr><td>Process offloading</td><td>Vehicles</td></tr>
<tr><td>Route planner</td><td rowspan="4">Near real-time</td><td rowspan="4">Publish/subscribe</td><td>Drivers</td></tr>
<tr><td>Pedestrian crossing planner</td><td rowspan="2">Local Authorities</td></tr>
<tr><td>Congestion management</td></tr>
<tr><td>Rouge node detection</td><td>Police</td></tr>
<tr><td>Traffic signal planner</td><td rowspan="2">Batch data</td><td rowspan="2">Pull-based</td><td rowspan="2">Local authorities</td></tr>
<tr><td>Traffic planner</td></tr>
</table>

reasoning, supervised learning and unsupervised learning. The reasoning stage is key to the algorithms such as clustering and pattern matching. For example, the specific time of the day, model and condition of the car, and driver's previous record can indicate whether the detected unsafe driving behavior of the driver will persist. In addition to collected context information from vehicles, drivers and environment, the fog analytics will be able to contact other fog nodes and cloud to get already stored context information about a specific vehicle or driver.

D. SERVICE LAYER

The service layer is responsible to stores, manage and expose the results of analytics to IoV applications. The data analytics layer passes its analysis and context information to service layer. The received data is analyzed and classified by the service layer. If the data is required a new service to expose based on its context information than service layer creates a new service and updates its service registry. Otherwise, the data is stored in relation to an existing service.

There are two most popular approaches to expose services to users: Service-Oriented Architecture (SOA) based and Representational state transfer (REST) based web services [39]. The SOA based web services uses Simple Object Access Protocol (SOAP) XML messages and offer transactional reliability. However, REST based (RESTful) web services are more flexible and offer variety of data formats while exposing them using standard GET, PUT, POST and DELETE methods. Therefore, we advocate using RESTful web services to expose data to application layer. The service layer also performs service composition to provide value-added services to applications.

E. APPLICATION LAYER

There is plethora of applications with different QoS requirements running at application layer. The applications can consume the web services from service layer using push, pull or publish/subscribe based strategies. The push strategy requires the service layer to push updates directly to applications, whereas pull-based applications pull information from service layer themselves. The publish/subscribe strategy access allow application to subscribe their interests and then the list of subscribers is notified about the service updates. These applications can be categorized in real-time, near real-time and batch data requirement-based applications. Table 4 illustrates few fog-based applications with their QoS requirements and users. The real-time applications require real-time QoS such as process offloading, and safety applications. These applications seek aid of fog nodes to help them perform the complex processing such as video processing from multiple sources. The push and publish/subscribe strategies are suitable for these applications. The near real-time applications are able to tolerate some delay in response such as route planning application, adaptive traffic signal scheduling applications. The pull or publish/subscribe strategies are applicable for the application. For example, a route planner application will perform with required efficacy even there is some delay in knowing that there is congestion in the next junction. The batch data requirement applications require some historic data related to the vicinity, and thus have low QoS requirement in terms of latency. The examples of these applications are hourly signal planner, and local shops deal advertiser. These applications mostly rely on pull based strategy to get data from service layer.

VI. USE CASE SCENARIOS

The proposed context-aware and data-driven framework allows fog nodes to gather, analyze and reason with the data collected from multi-sources in IoV. There are several applications that can be enabled by this framework. This section discusses the use-case scenarios that are enriched by the context-aware fog-based services.

A. REAL TIME USE CASE SCENARIO

Iain travels back from his work around 5 pm daily on his smart car that takes him 45 minutes. After a busy and hectic day, he was travelling back to his home. Suddenly, he received a notification from his car to slow down, so he followed the caution. In few moments, he saw a kid unanticipatedly appeared on the road from a street while running after a ball. He could fully stop at the right time because of his reduced speed.

At the next traffic light, he noticed that his route is updated based on the feedback of the network. He was informed by the route-planner application that the route was updated because of the sudden congestion that may be caused by a delivery truck that is stuck on the road. Few miles before his home, he received an advertisement from a local petrol station that was offering free car cleaning with every full refueling. He decided to avail the offer as his car required a refueling.

In this scenario, three fog-based applications are used to ensure safety, efficiency, and convenience for the user. The sudden appearance of the kid was predicted by a cognitive fog service based on the real-time analytics of data gathered from local street video cameras and the context information of the car. The user's application coupled the fog service's feedback with the car's location and speed to avoid an imminent accident. The dynamic route planner application was getting a real-time update about the road condition based on its context from a fog service to identify a congestion pattern based on the truck's slow movement and number of vehicles on the road. The fog-based advertising application is aided by a fog-based service that knows the vehicle fuel status to advertise the user with the offer before the user can pass the petrol station based on the current context of the user.

B. NEAR REAL TIME USE CASE SCENARIO

Dubai downtown is the busiest area in Dubai that gets maximum traffic in the peak work hours. Drivers are facing traffic jams for long times. Frequent accidents are occurring in the area due to heavy traffic. Road and Traffic Authority (RTA) in Dubai has to depute traffic wardens on regular basis besides having traffic signals to ease the flow of traffic. In case of an emergency vehicle, the situation gets worse due to traffic jams and emergency vehicles are stuck in the jams that causes serious inconveniences at times.

RTA decided to use Adaptive Traffic Signal Management utilizing Fog units. The fog units are deployed at each traffic signal in the area to collect and store GPS coordinates of the vehicles, and motion sensor readings. The collected information is pre-processed by filtering the required information which is then analyzed by the analytical layer. Based on the analysis of the data stored and collected, the Adaptive Traffic Signal Management application changes the state of the traffic signal from Red to Green and vice versa. The traffic signals for the roads that are experiencing heavy traffic are turned green more frequently than the roads with less traffic density. The traffic signals adapt this behavior based on the analysis of the data stored in the fog nodes for previous hours and sometimes previous days on the same hours to ease the flow of the traffic. Similarly, the Adaptive Traffic Signal Management application is designed to give priority to emergency vehicles throughout the day. A traffic signal with an ambulance approaching will be given highest priority even if the traffic density is less on that traffic signal.

Adoption of Adaptive Traffic Signal Management utilizing Fog nodes has helped RTA in efficiently managing the traffic on road by avoiding long traffic jams and frequent accidents.

VII. CONCLUSION

The advent of latest technologies has enabled connected vehicles paradigm that offers range of real-time safety and other applications. This connectivity aids collaboration between vehicles and available network infrastructure to generate and share data. This diverse user and context data have potential to provide information for decision making. The traditional centralized cloud-based intelligence in VCC provides the capabilities require to deal with the big data analytics, storage and management. However, it fails to meet the real-time or near real-time requirements of novel applications due to delay caused by multi-hop communication. These novel applications such as adaptive signal scheduling and safety applications require response in real-time or near real-time. These requirements become more challenging in IoV system due to high mobility of its entities. The proposed data-driven framework deals with these issues by collecting, preprocessing and analyzing data based on its context at fog layer of IoV architecture. The analyzed data is made available to applications using RESTful web services. The framework employs push, pull or publish/subscribe based service consumption strategies to support real-time, near real-time, and batch data based IoV applications.

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