Geospatial Edge-Fog Computing: A Systematic Review, Taxonomy, and Future Directions

Jaydeep Das, Soumya K. Ghosh, and Rajkumar Buyya

Abstract Real-time geospatial applications are ever-increasing with modern Information and Communication Technology. Latency and Quality of Service-aware these applications are required to process at the edge of the networks, not at the central cloud servers. Edge and fog nodes of the networks are capable enough for caching the frequently accessed small volume geospatial data, processing with lightweight tools and libraries. Finally, display the image of the processed geospatial data at the edge devices according to the user's Point of Interest. Several kinds of research are going on edge and fog computing, especially in the geospatial aspects. Health monitoring, weather prediction, emergency communication, disaster management, disease expansion are examples of geospatial real-time applications. In this chapter, we have investigated the existing work in the edge and fog computing with the geospatial paradigm. We propose a taxonomy on related works. At the end of this chapter, we discuss the limitations and future direction of the geospatial edge and fog computing.

Keywords Edge computing · Fog computing · Geospatial applications · Geographical information system (GIS) · Survey · Taxonomy

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1 Introduction

With the proliferation usage of smartphone and IoT devices, generating, accessing, and analyzing geospatial data becomes a regular activity. To access and analyze these geospatial data, computing and processing resources are required [1]. The provision of resources is varied based on applications. For the large computation, a huge infrastructure is needed for processing a large amount of geospatial data. In such cases, the central cloud computing infrastructure is the only solution. IoT devices have not enough capacity to do so [2]. However, for the small amount of geospatial data processing, analyzing, and decision making, edge, and fog computing is a promising technology [3].

A pictorial view of the cloud, fog, and edge computing with geospatial applications is presented in Fig. 1. Cloud is the core layer where high-end computing servers and databases are present. Users receive virtualized computing instances

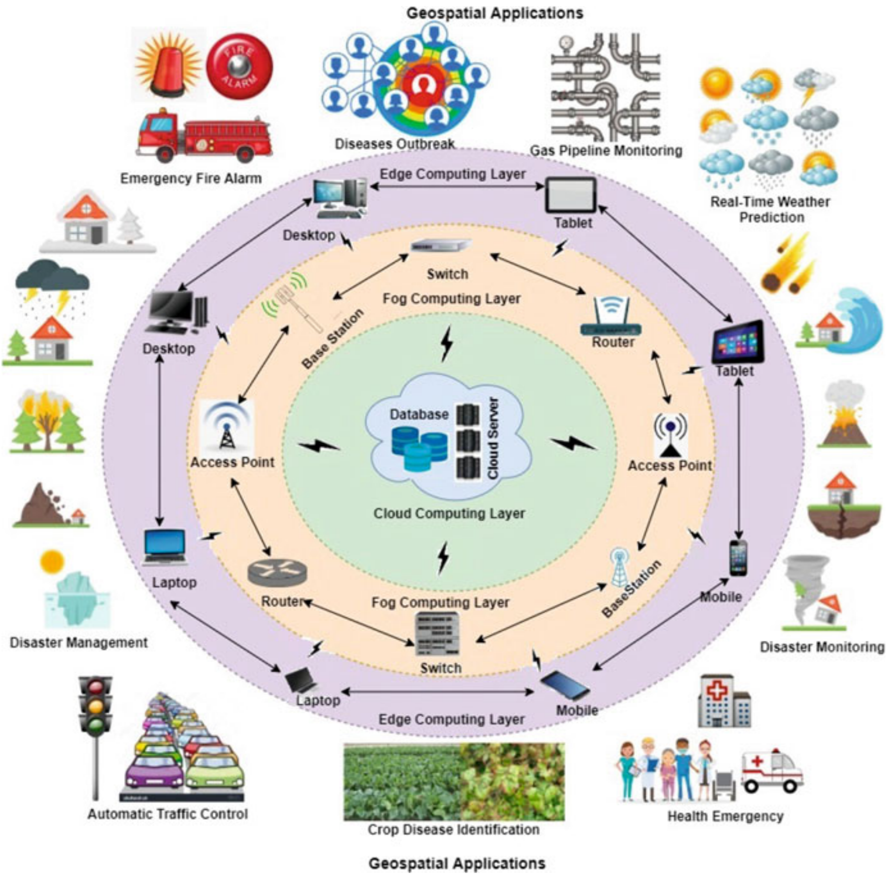

Fig. 1 Geospatial cloud-fog-edge computing layers

with different configurations for their geospatial applications. Moreover, Cloud is present multi-hop distance from geospatial applications.

In fog computing layer, the computation is done in any of the fog nodes i.e., switches, routers, gateways, access points, base stations [4]. These fog nodes are present in between the edge devices, i.e., mobile phone, laptop, tab, and the central cloud server. These fog nodes are capable to compute and analyze the small amount of geospatial data. After processing and analysis of the geospatial data, these fog nodes generate a quick decision to the edge devices. Fog computing is effective in terms of service delay, energy efficiency, network congestion, etc.

Edge computing layer is constructed by the inter-connectivity among nearby edge devices like mobile phones. As edge computing is very near to the edge devices, it facilitates high network bandwidth, ultra-low latency, and real-time response [5, 6] to the geospatial applications like sending alert to the fire station, change the color of traffic signal lights and its timespan, sending a message to the medical person about his/her patient's condition, spread awareness to the fisherman before the tsunami, make attentive to the workers of the gas station about the leakage of methane gas from pipeline [7].

Edge and fog computing (EFC), enriches the computing paradigm for real-time geospatial applications like health monitoring [8–10] systems, sort-term weather prediction, disaster recovery [11, 12], crop diseases monitoring [13]. In all these cases, a quick decision has to be taken depending upon the analysis of captured geospatial data by edge nodes [14]. The response time is a major concern in all of the above situations. Fast decisions can be obtained from a geospatial EFC system than a central geospatial cloud system. Geospatial fog computing helps in the computation of geospatial data, analyzing the data. Return results or alert to the users within a stipulated time duration by the edge nodes. A layered architecture has been proposed in [15]. EFC system has an inner, middle, and outer edge layer. Different edge and fog devices are present in these three layers.

In summary, motivations move towards the Edge-Fog than cloud-centric computing paradigm are low latency or response-time, less network bandwidth utilization, uninterrupted service due to minimum distance from edge devices, resource-constraint at the individual edge devices affects cloud performance, and security of the edge devices is not controllable by cloud from distance [16].

In this chapter, we present a taxonomy based on a survey of Geospatial based Edge-Fog computing. There are many surveys exist in edge and fog computing domain [2, 17–37], but none of them address geospatial aspects. In Sect. 2, we have discussed the geospatial related researches in Cloud, Cloudlet, Mist computing environment. A taxonomy on existing research work in geospatial edge and fog computing has been structured in Sects. 3 and 4 makes a summary of these works in a tabular form for better understanding. Section 5 expresses the limitations in the geospatial edge-fog computing domain. Future scopes of geospatial edge and fog computing is explored in Sect. 6. The conclusion of this chapter has been done in the last section.

2 Existing Computing Paradigms

In this section, we focus on ongoing researches on cloud computing, cloudlet, mist computing with geospatial features.

2.1 Geospatial Cloud Computing

Currently, there are many computing strategies are available. Cloud computing [38] is the core of all these computing, where a large number of servers, databases are available. While huge computing is required for a geospatial application, then cloud is the only option for processing it. As the cloud servers reside multi-hop distance from the geospatial application nodes, it increases the overall communication delay which is sometimes critical for real-time geospatial applications like methane gas leakage monitoring, fire alarming, health monitoring [10]. The characteristics of the Cloud-GIS has been mentioned in [39], which are the extensible geospatial version of the cloud characteristics. These are—(i) elasticity of geospatial resources, (ii) on-demand geospatial services, (iii) measurable and pay-as-you-go for geospatial resources, i.e. geospatial data, geospatial tools, (iv) accessing diversity, (v) transparency, (vi) service based geospatial applications, and (vii) hardware and resource extendable. The geospatial based Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS) are discussed in [40]. Along with these geospatial Data as a Service (DaaS) is also a major concern. Some geospatial services on the cloud are also mentioned in [41]. OGC compliant geospatial service orchestrations in the cloud have been done in [42] for geospatial query resolution. Cloud-based GIS architecture models have been discussed in [43–45]. Geospatial data indexing [46, 47] is performed for better data management in the cloud. Geospatial data interpolation [40, 48] is performed in the cloud for determining the missing geospatial data in the public dataset. Geospatial data mining [49, 50] and data processing [51–53] are performed for the getting results of the geospatial data query [54–56]. All these geospatial data mechanisms have been done for getting the results from the geospatial applications running over the cloud computing platform.

2.2 Geospatial Cloudlet

Cloudlet is introduced to improve the latency of the cloud by caching the copies of data while users access the mobile applications [57]. It brings the performance of the cloud closer to mobile users. Cloudlets are computationally less powerful than the central cloud system [58]. Mobile phone, Laptop, an Access point can be used as a cloudlet. If many cloudlets are connected with each other, then the single point of failure can be avoided. Cloudlet supports mobility. The mobile device offloads the codes to the cloudlet and the code is migrated to another nearby cloudlet. While the mobile device reaches under the coverage of the second cloudlet, it starts getting the executed results from the second cloudlet [59]. Location-based service discovery is done by the distributed cloudlets [60] and it generates less traffic in the network than a cloud-based approach. Geospatial query resolution using a cloudlet is performed in [61]. This approach reduces delay and power consumption than remote cloud access for geospatial data analysis.

2.3 *Geospatial Mist Computing*

According to [62], Mist computing is a computing layer between fog and cloudlets. Sensor and actuator devices are involved in the processing of data, which pushed the computing towards the edge node of the network [63] where edge devices are present. This reduces the communication latency within edge devices in milliseconds. Mist computing enhances the self-awareness among the edge devices in such a way that edge devices perform their operations with unstable Internet connections [15]. A Mist-GIS framework has been developed for clustering and overlying the geospatial data of the Ganga river basin [64] and malaria disease spread in the state of Maharastra, India [65].

2.4 *Discussion*

The changes of different parameters like distance from applications, computational capacity, cost, energy savings, real-time responses, etc. with respect to computing paradigms are represented in Fig. 2. However, communication delay, computational capacity, the infrastructural cost is more in a cloud environment than the other computing paradigms. Moreover, energy efficiency, closeness to the applications, and real-time response are promising in the edge, fog, and mist computing.

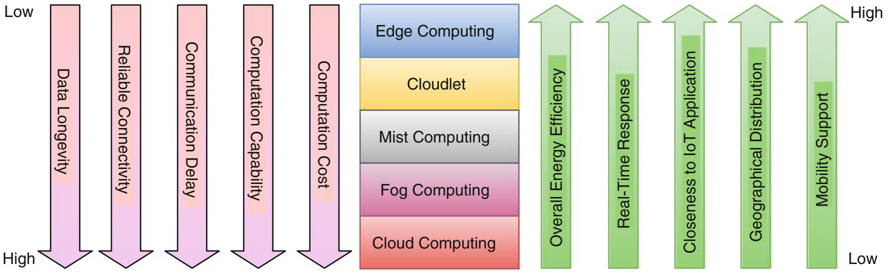

Fig. 2 Different computing layers with parameters

3 Taxonomy

We have represented a taxonomy on geospatial Edge-Fog computing in Fig. 3. This taxonomy is based on the existing works in the geospatial domain where the computation has been done in Edge and Fog computing environment. We have categories the works into four parts. These are-

- *Geospatial Computing:* We focus on service and resource management in edge-fog environments. Resource management is sub-categories in power, delay, cost, and geospatial data management. Whereas, service management is broken into four parts, i.e., network, application, geospatial data service, and quality of service management.
- *Geospatial Data:* The geospatial data which used for the applications running on the Edge-Fog computing are mentioned.
- *Geospatial Analysis Procedures:* The methods or procedures applied to the geospatial data, which help to identify the emergency or severity of the situations through the geospatial applications.
- *Geospatial Applications:* Different types of geospatial applications which run on the edge and fog computing environment.

In the following subsections (Sects. 3.1–3.4), we elaborate existing related works that fall into the four categories mentioned above.

3.1 Geospatial Computing

In this section, we discuss about the overall edge and fog computing management. It includes resource management, and service management.

3.1.1 Resource Management

Resource provisioning has been done depending upon the power, delay, cost by the edge, and fog nodes. Also, keep in mind about the amount of geospatial data can be processed and stored by the edge or fog nodes [19].

Power Management Edge and Fog computing paradigm are introduced to efficient power management of the overall network system. In [3, 66–68], the processing of geospatial data is done at the edge and fog devices of local region. Data processing at local devices reduces the data transfer to the remote cloud server. This leads to low power consumption in the overall system.

Delay Management Delay in communication or in service is crucial for applications. Sometimes, an application loses its relevancy due to the delay. This is one of the major concerns that introduce Edge and Fog computing instead of Cloud

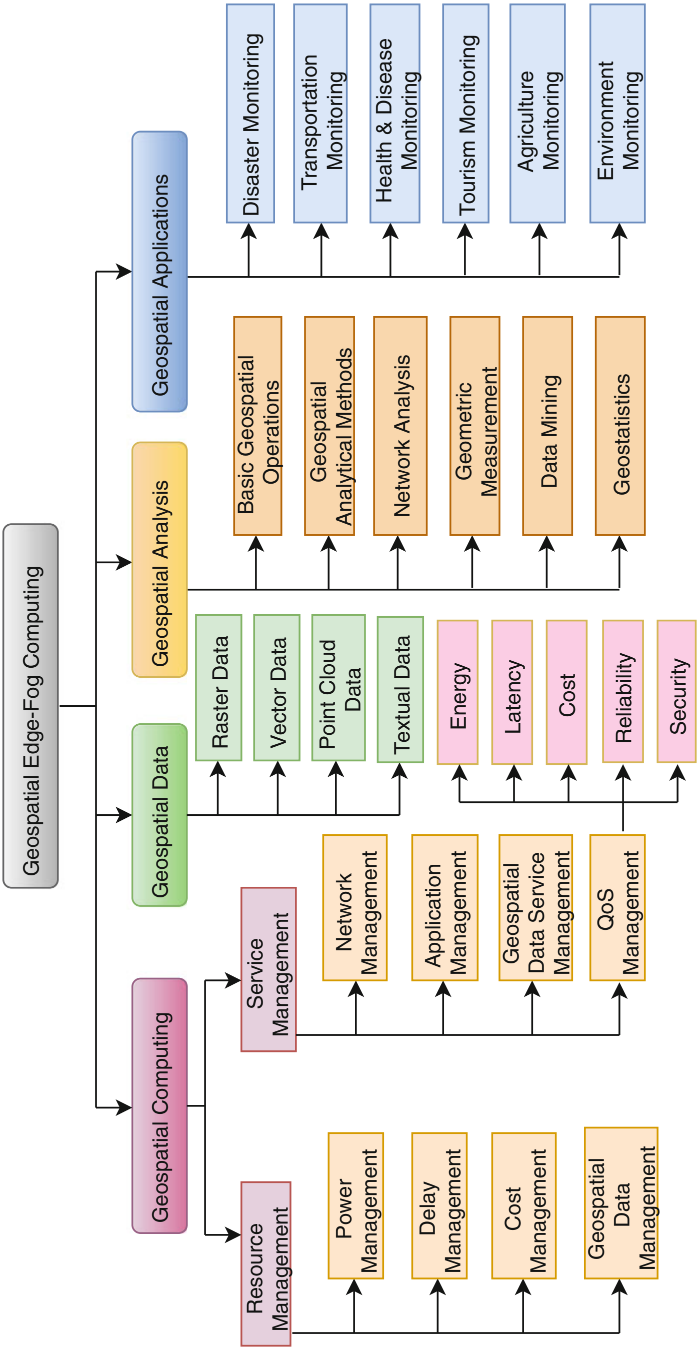

Fig. 3 Taxonomy of geospatial edge-fog computing

computing. In [66], geospatial queries are resolved within nearby Fog devices if concern data is available that fog devices. Otherwise, fog devices communicate to the cloud server for processing. They achieved 47–83% improvement in delay than the only-cloud environment. The shortest path within the critical zone has been determined in case of emergency situation [68] within nearby fog devices. They come by 9–11% better in average delay than the cloud platform. In time-critical applications [67], achieve improvement in delay on user devices as the processing of information done in nearby fog devices.

Cost Management The cost management includes infrastructure deployment cost, networking, or communication cost, and application execution cost [24]. Data offloading cost, process migration cost are also considered for this category.

Geospatial Data Management GIS applications are running based on geospatial data. These data are large in volume [69]. Only pre-processing of data can be done in edge and fog nodes because the infrastructure like memory, processor, storage capacity is small. Pre-processed data forward to the cloud for further processing. Sometimes, frequency used data are only cached in the edge and fog nodes, which helps to reply quickly to the user query. Various methods for matching geospatial vector data are mention in [70].

3.1.2 Service Management

We discuss network management, application management, geospatial data service management, and quality of service(QoS) management as overall service management of the Edge-Fog computing environment.

Network Management Networks are managed in the EFC paradigm through congestion control, seamless connectivity, and network virtualization. Congestion in the network can be avoided by minimizing the communication with the cloud server from the EFC network. Geospatial application requests are coming from any edge devices, and its resolution performed nearby edge or fog nodes. It leads to minimizing network traffic. Seamless connectivity helps to connect edge devices with cloud or fog servers without any latency. Seamless connectivity is possible with handover technology in future vehicular networks [71, 72]. Network virtualization has been done by the software-defined network (SDN). Network function virtualization (NVF) helps to virtualize the traditional network functions. SDN based work in fog computing done in [73, 74].

Application Management Real-time geospatial applications are road traffic monitoring, weather prediction, a spatial query against any point of interest (POI), emergency health monitoring. In all these cases, a cluster of reliable edge-fog nodes, low latency, and dedicated computing resources are required. Augmented reality (AR), real-time video streaming, content caching technique, bigdata analysis discussed in [75]. Using *offloading* technique [76], one nearby edge/fog nodes can forward computational tasks to its adjacent edge/fog node which has better computing resources. *Scaling* is another aspect that helps to run the application smoothly. Always the processing of geospatial data amounts is not the same. When it increases, the computation power needs to increase. This leads to a challenge for edge/fog nodes. In the case of scalability, cloud is still a promising technology.

Geospatial Data Service Geospatial data are integrated from various sources through OGC compliant web services [77]. There are five types of web services available. These are Web Feature Service (WFS), Web Processing Service (WPS), Web Coverage Service (WCS), Web Map Service (WMS), and Catalogue Service for Web (CSW). WFS helps to extract the features according to queries. WPS applies different spatial operations over geospatial data. WMS displays the maps according to user demands. CSW prepares the registry of the available data sources.

QoS Management Best quality of service is achieved in EFC through energy-efficient computation, low latency in communication, overall minimal cost, reliable, and secure connection.

- *Energy:* In the EFC paradigm, energy is consume minimize through energy-aware computation offloading, mobility management federation of constrained devices [35]. In [21], the overall edge computing system will be energy efficient through edge hardware design, computing architecture, operating system, and middleware.
- *Latency:* Computation latency and communication latency are considered for overall service latency management. Computation latency depends upon the configuration (Processor, RAM) of the edge and fog nodes. Whereas, communication latency relies on network bandwidth. It can be considered as within edge nodes, edge node to Fog node, and within fog nodes connectivity.
- *Cost:* It is the summation of the computational cost, deployment cost, and networking cost. Network bandwidth is responsible for the networking cost [78]. Whereas, computing devices like processing unit, RAM, virtual machine cost are considered as computational cost. Deployment of edge-fog nodes and their communication elements expenses come under the deployment cost.
- *Reliability:* It is also the main concern while an application is running on reliable edge or fog nodes. The availability of such computing nodes should be guaranteed. In [35], mentioned to make a fog service reliable the replication of required functions is required, but it may not possible due to the limited computing resources available to the fog devices. So, it is a challenge to make a service reliable and available which is running in edge and fog devices.
- *Security:* Heterogeneous and geographically distributed edge and fog nodes have a major concern about the security. Rogue fog node identification, authentication, strengthen the network, and data storage security are ways to constitute a security in the edge-fog environment [79]. There are various security attacks, like Man-in-the-middle, Distributed Denial-of-Service (DDoS), ripple effects, Injection attacks [33, 80] can be done through unauthorized access of user [81, 82]. Before deployment of any geospatial applications in the EFC system, the four basic security requirements, i.e., availability, authenticity, confidentiality, and data integrity should be verified.

3.2 Geospatial Data

Geospatial data has its geographic location (latitude/longitude) attached to it. These data are captured from different types of sensors. It is also captured by the high-resolution cameras from the satellites. Raster and vector data are primary data format [83], but in [69] types of geospatial data are extended with Point Cloud data and Textual data along with prior two categories.

Raster Data It is made up of a grid of pixels and each pixel has an individual value. All kind of aerial photography and satellite imagery comes into this category. It includes thematic cartographic maps, topographical maps, orthophotos, time series of satellite images.

Vector Data It is made up of the point, polyline, polygon. It has a shape feature, which contains the (x, y) coordinates. The shape contains latitude, polyline longitude information instead of (x,y) while the representation is done on earth surface with 2D view.

Point Cloud Data This kind of data helps to visualize the 3D model of the terrain. Terrestrial Mobile Mapping System (MMS) data [84], LiDAR data are examples of point cloud data [85].

Textual Data Text data are generated from several applications with location-tagged [86]. Social media data like Twitter, Facebook data, online blogs are coming into this category. These help to generate data-driven geospatial semantics.

3.3 Geospatial Analysis Procedures

Geospatial analysis [87, 88] is required for visualization of the geospatial data by using software and tools. The geospatial analysis methods are described below.

Basic Geospatial Operations Buffer creation, nearest neighbor searching, overlay analysis are the basic GIS analysis tools. Overlay of the several geospatial layers has been done based on user queries. It reduces the overload of the computer memory displaying selected data layers instead of all layers. The clip, Intersect, Union are the basic overlay tools. Whereas, the buffering technique is used to identify the affected areas in flood [89], forest fire [90], earthquakes [91], tsunami [92], or disease outbreak like malaria, dengue fever [93], corona etc.

Geospatial Analytical Methods It includes the clustering of the similar point patterns, generation of the heat map, analysis of points density. These methods help to identifying city traffic flow [94], air quality determination [95], monitoring of greenhouse gas emissions from factories, households, livestock agriculture [96].

Network Analysis This type of geospatial analysis is based on graph analysis, where the connection between edges and nodes are defined. Transportation problems can be solved by finding the shortest path between two cities connected by a road network, or rail network, or a combination of both networks. This shortest-path generation helps in healthcare facility [97], tourism facility [98]. Human movement pattern identification after analyzing the trajectories in the road network has been done in [99, 100].

Geometric Measurement Distance and proximity between one point to another point is the basic geometric measurement which is vastly used in the GIS applications. This measurement helps in tourism facility recommendations [101] like nearby hotels, restaurants, visiting places, ATM. It also helps to find nearby hospitals, medical shops in heath-care applications [67, 102]. In disaster management, transfer the victims to the nearby shelters, or reach to the victims with relief [103, 104].

Data Mining A large number of geo-tagged data generate from sensor nodes, drone images, mobile devices, crowdsourcing, etc. Data mining is a technique to generate information after analyzing such unstructured geospatial data. It helps to identify human movement pattern [100], urban growth over a time period [105], smarter traffic light control during time zones [106], wildlife monitoring [107].

Geo-statistics Spatial interpolation is a geo-statistics technique [108] to analyse the surface. This technique estimates the value of an unknown point with the knowledge of nearby known point's value. Kriging [109], Inverse Distance Weighting (IDW), Regression are well known geospatial interpolation techniques. Using these techniques, many geospatial related work like malaria-prone zone identification [110], heavy metal, i.e. zinc, soil contamination [111], recognize area of irrigation water [112] for agriculture had been done.

3.4 Geospatial Applications

Here, we have discussed some geospatial applications which are run on the edge-fog environment or run on the cloud environment with the support of EFC.

Disaster Monitoring Disaster prediction data are stored in telephone central offices (TCOs). These data are important for disaster monitoring. To prevent data loss, a data distribution technique among nearby edge devices has been proposed in [11]. They have used Japan Tsunami prediction data. In [113], identify the missing people in the disaster recognizing by face. To save the energy and network bandwidth only significant facial images are sent to the cloud server. Identifying the disaster-prone area after analyzing geospatial videos and satellite images in fog-cloud environment [12].

Transportation Monitoring A traffic management system [114] is developed where RSU and vehicles (both parked and moving) act as fog nodes according to the queueing theory. They scheduled traffic flow among fog nodes and tried to minimize the response time to make it real-time traffic management.

A mobility pattern of moving agents predicted after applying a machine learning algorithm on spatio-temporal mobility data [67, 115]. It helps to predict the next location of the moving agents, which added advantage for Time-Critical Applications.

A prediction model [94] is generated after analyzing of Bing Maps traffic jam information, and manage traffic flow in the Chicago city.

A smart traffic lighting system is proposed in [106], which is to optimize the management process. The lighting time changes according to the traffic conditions of the roads. It reduces human errors in signaling.

Health and Diseases Monitoring Indoor, outdoor patient's continuous health monitoring is necessary. Mukherjee et al. [116] proposed a cloud-Fog based solution for health monitoring with mobility data of patients while he/she is an outdoor location. Any small health data analysis has been done by fog devices, but any critical data analysis and mobility data analysis has been done in the cloud server.

A heart disease identifying, HealthFog [117], architecture has been developed with deep learning technology. They used FogBus for real-time data analysis by integrating the IoT-Edge-Cloud environment with delay and energy efficiency. Malaria [65, 110], dengue fever [93] prone zone identification with geospatial map and taking action accordingly are some aspects in this category.

Tourism Monitoring Geo-tagged Flickr images are mining to detect the accurate tourist destination in [118]. RHadoop platform helps to organize such big spatial tourism data in the Cloud platform. A mobile-based tourist recommendation system has been developed in [101]. A tourist guide application for Cyprus is discussed in [98].

Agriculture Monitoring Vatsavai et al. [119] synthetically generates images of crop fields. With the anomaly detection, feature extraction, and unsupervised technique, they identified the Weeds and crop diseases. Omran et al. [112] proposed an irrigation water quality evaluation method for agriculture in the Darb El-Arbaein area. They classified water quality depending on the salinity of the water. The computed index value determines the quality of the water. High index (above 70) is good for irrigation, where the lower index (below 40) is bad for irrigation. A livestock agriculture analysis has been done by [96]. They analyze the dataset of biodiversity, climate, water, land, people, farms, and animals using the cloud server.

Environment Monitoring The presence of excessive Carbon Monoxide (CO) gas in the air is a cause of environmental pollution. Monitoring of CO level increment in pollution-prone areas is developed an application of Fog computing [120]. They used krigging methods to identify the distance among CO emission areas, calculated and plotted on Google map using lat/lon information. Air quality also have been checked at low concentration levels in [95] using AirSensEUR.

Various mineral resources of India are determined after data mining of spatial big data and displayed resources using overlay analysis in the QGIS tool [121]. They also have done Ganga river management using mist Computing.

4 Existing Work on Geospatial Edge-Fog Computing: A Glance

We have summarised the existing geospatial applications on the edge and fog computing domain in Table 1. Here, we pointed out the existing papers in the first column. Second column is said about the edge and/or fog nodes used in their work. Other computing paradigm, devices applied in different works are presented in the third column. Fourth column describes the used data in works. In the last column, the geospatial applications had applied in the corresponding research work.

A large number of applications are associated with Geospatial Edge-Fog domain. Methane gas leakage monitoring [7] has been done with collected sensor data by wireless sensor network (WSN) and IoT devices. The data are processed in Raspberry Pi devices and identified the abnormal sensor data from gas leakage areas. In other work on CO gas level monitoring [120], gas sensor data are collected through Mikrokontroller ESP 8266, Access point, MiFi, and data analysis has been done and stored in the Cloud server.

Healthcare applications in EFC has been proposed in [116]. They used health data of various aged group students using Internet of Health Things (IoHT) and stored data in Cloud. Raspberry Pi is used for primary health data analysis. Tuli et al. [117] used patients' heart data for identifying health disease. They used FogBus tool for analysis heart data.

Trajectory data collection for various IoT applications has been elaborated in [122]. They used taxi trajectory data for analysis. The data collection and analysis have been done through edge nodes and fog servers respectively. Real-time traffic management has been proposed by Wang et al. [114]. Road side units(RSU) collects the real-time data of the roads and analysis in nearby cloudlet. The final data are stored in the Cloud.

Time-critical application [67] and mission-critical application [68] has been proposed in EFC domain. Mobility data is analysed to predict the location of the user in a critical time. So that the facility can be provided to the user easily. They used mobile devices for tracking the user location and stored in Cloud. On the other hand, simulated data, and nodes are used for critical mission applications. They used K* heuristic search algorithm for determining the shortest path to reach the critical location for the defense sector.

Different types of image data are analysed in EFC for several applications like disaster situational awareness [12], nanosatellite constellations [123], metropolitan intelligent surveillance [124]. Satellite image data are used for first two applications.

Table 1 Existing work in geospatial edge-fog computing

Work	Edge/fog nodes	Associated computing	Considered data	Applications
Klein et al. [7]	Raspberry Pi	WSN, IoT	Sensor data	Methane gas leaks monitoring
Nugroho et al. [120]	Mikrokontroller ESP 8266, Access point, MiFi	Gas sensor, Cloud server	CO gas sensors data	CO gas level monitoring
Mukherjee et al. [116]	Raspberry Pi	Cloud, IoHT	Student health data	Personalized healthcare
Tuli et al. [117]	FogBus	Cloud, IoT	Heart patient data	Heart diseases monitoring
Cao et al. [122]	Simulated edge nodes	Fog server	Taxi-trajectory data	Trajectory data collection for IoT applications
Wang et al. [114]	RSU	Cloud, Cloudlet	Taxi-trajectory datasets	Traffic management system
Ghosh et al. [67]	Mobile device	Cloud, IoT	Mobility data	Time-critical application
Mishra et al. [68]	Simulation node	WSN, Cloud	Simulated data	Mission critical applications
Chemodanov et al. [12]	Not mentioned	Cloud	Video and satellite image data	Disaster situational awareness
Denby et al. [123]	Jetson TX2	Image sensor	Satellite image data	Nanosatellite constellations
Dautov et al. [124]	Raspberry Pi 3	Cloud	CCTV image data	Metropolitan intelligent surveillance system
Barik et al. [121]	Raspberry Pi	Cloud	Mineral resources data	Mineral resources information management
Vatsavai et al. [119]	Lenovo ThinkStation P320 with GPU	Not mentioned	Synthetically generated image	Weeds and crop diseases identification
Armstrong et al. [125]	Clusters of sensors	IoT sensors, Cloud	Safecast data	Ionizing radiation risk detecting
Richardson et al. [126]	Raspberry Pi-2B, Pi camera	Single board computer	Raster data	Solar forecasting
Tsubaki et al. [11]	Telephone central offices(TCO)	Not mentioned	Japan tsunami prediction data	Data loss prevention in natural disasters.
Barik et al. [127]	Intel Edison	GIS Cloud	Global map data	Different compression techniques over GIS data
Das et al. [66]	Mobile, Laptop	Cloud (GCP)	Road network, rail track, forest data	Geospatial query resolution
Higashino et al. [128]	Cyber physical systems	IoT, Laser range scanner	Not mentioned	Safety management, and vehicle speeds prediction
Liu et al. [113]	Edge server	Cloud, IoT device	Face image data	Missing people search
Liu et al. [129]	Performance oriented edge computing (POEC)	IoT	Not mentioned	Multi-scale 3D scenery processing

Whereas, CCTV image data is used for the intelligent surveillance application. Jetson TX2 and image sensors are used for nanosatellite constellations.

Mineral resources data are captured and analysed in Raspberry Pi and Cloud for providing mineral resources information management [121]. For weeds and crop disease identification [119], Lenovo ThinkStation P320 with GPU has been used to process various high definition synthetic crop images. Safecast data processed for ionizing radiation risk detection [125] and Japan tsunami prediction data analysed for data loss prevention in natural disasters [11]. Solar forecasting [126] has been done with the analysis of raster data in Raspberry Pi-2B and single-board computers. Raster data captured through Pi camera.

Geospatial query processing [66], and different compression techniques [127] over GIS data are done using EFC. Several geospatial queries are done over road network, rail track, forest data. Delay and power consumption has been calculated for different types of geospatial queries. For the compression technique, global map data has been utilized.

5 Limitations in Geospatial Edge-Fog Computing

Every domain has its limitations. We will discuss here the drawbacks of geospatial edge-fog computing.

- Geospatial data are large in volume. It is difficult to store and process it in small computing infrastructure, i.e., EFC. Whereas, the cloud has the advantage of a large data store.
- Large computation is required for geospatial prediction and analysis. Sometimes this cannot be fulfilled by EFC.
- Small number of simulation tool, like iFogSim [130, 131], FogBus [132] for EFC is available.

6 Future Directions

In this section of the chapter, we discuss the future directions of the geospatial EFC research work. Though many explorations have been done in the edge and fog computing, very little progress happened with the geospatial domain. Still, we can think about the following aspects of geospatial Edge-Fog Computing in the future.

- Investigation of pricing policies is required individually for geospatial data providers and Edge-Fog computing service providers.
- Geospatial data management in the EFC environment is a challenge. Keeping a small amount of data within the edge and fog nodes of a distributed manner and synchronize them.

- Geospatial application management, EFC resource provisioning, with artificial intelligence and machine learning technique can be a future trend.
- Every geospatial application, i.e., weather prediction, health-care, crop analysis, etc. has its own requirements that are different from each other. Application relevant policies are required for proper management in the EFC environment.
- Automatic orchestration of different geospatial web services to resolve any geospatial query in the EFC domain can be future aspects.

7 Summary

In this chapter, we have discussed the existing works on the Geospatial Edge-Fog computing domain in detail. We provide a taxonomy over geospatial EFC which considered about the different types of geospatial computing management, geospatial data types, geospatial analysis methods, and geospatial applications. We provide a brief of geospatial EFC existing work in a tabular form. After that, we have discussed the limitations of the geospatial EFC. We ended our discussion with future possibilities of geospatial EFC.

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