

Geolocation-Centric Information Platform for Resilient Spatio-temporal Content Management

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SUMMARY In IoT era, the growth of data variety is driven by cross-domain data fusion. In this paper, we advocate that “*local production for local consumption (LPLC) paradigm*” can be an innovative approach in cross-domain data fusion, and propose a new framework, geolocation-centric information platform (GCIP) that can produce and deliver diverse spatio-temporal content (STC). In the GCIP, (1) infrastructure-based geographic hierarchy edge network and (2) adhoc-based STC retention system are interplayed to provide both of geolocation-awareness and resiliency. Then, we discussed the concepts and the technical challenges of the GCIP. Finally, we implemented a proof-of-concepts of GCIP and demonstrated its efficacy through practical experiments on campus IPv6 network and simulation experiments.

key words: *geolocation-centric, cross-domain data fusion, local production for local consumption*

1. Introduction

Advances of sensor devices and communication technologies are bringing the CPS (Cyber-Physical System)/IoT (Internet of Things) into a reality. Physical “things” are digitized by diverse and massive number of devices and the information generated by those things is collected into the cloud as “big data”. New insights are derived by applying

AI processing to big data, helping human activity to harmonize with the physical world.

In order to efficiently perform data mining, the preparation of cleaned, parsed, and formatted data is essential [1]. However, since current IoT systems are largely isolated within each individual vertical domains due to lack of standardization and interoperability, a horizontal IoT platform enabling cross-domain data fusion becomes critical challenge in collecting huge amount of data [2]. Many countries including US, EU, and Japan are currently engaged in the discussion of the requirements for cross-domain fusion. A noteworthy effort exists in the collaboration of the cross-domain data for smart cities [3] sharing such data as environmental data (i.e., map and temperature) and user behavioral data (i.e., trajectory and interests). Major challenges for the cross-domain data fusion remain:

- (a) Privacy issues for user behavioral data
- (b) Incompatible policies and standards among IoT service providers
- (c) Isolation of facilities and infrastructure between network operators.

For (a), the “user’s trajectory, interests, and preferences data” are regarded as a part of “personal data” in many countries. EU ratified new rules for personal data treatment (i.e., GDPR: General Data Protection Regulations) in 2016, and started already its operation since 2018 [4]. The GDPR permits the processing of the personal data only for the important public interest of the Union or of a Member State. Other countries including Japan are anticipated to follow this trend with the mandate to handle personal data “in the consideration of geographical area”. Although several efforts on data platform such as FIWARE [5] have accelerated the collaboration on cross-domain data, they are still limited to “open (processed) data”. That is, none of existing platforms treats the personal data. As a result, many developed countries have recently started the discussion on the utilization of personal data and announced the concept of data platform to treat the personal data at the nation level. In general, the current platforms treat personal data with user’s permission, but are operated by different IoT service providers for a specific purpose as described in (b) above.

Note that some of environmental and personal data suitable for the cross-domain data fusion such as map and residential address are generated and managed in the geographical proximity (e.g., city and prefecture). Therefore,

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we advocate the “*local production for local consumption (LPLC) paradigm*” as a viable approach for cross-domain data fusion. In this regard, Edge Computing [6] can function as data anchor point for cross-domain data fusion. However, as Telecom companies have their own network infrastructures, the feasibility of data sharing in a geographical service area is low due to a monopolistic stance in practice. It is also difficult for IT companies to place their own facilities to the Telecoms’ network edge (described in (c) above). Consequently, the cross-domain data fusion even in a small region is a remote possibility at the moment.

Therefore, we propose a new framework, geolocation-centric information platform (GCIP) that can produce diverse contents derived spatio-temporally from cross-domain data fusion and deliver them to users within a small region. Note that the contents produced by the GCIP are referred to as the spatio-temporal contents (STCs) in this paper.

The rest of the article is organized as follows. We first review the related works in Sect. 2. The concept of the GCIP is discussed in Sect. 3. We then clarify the essential functions and discuss technical issues with the proposed GCIP in Sect. 4. The experimental results on our proofs-of-concepts (POCs) implementation are explained in Sect. 5. Finally, we conclude this article in Sect. 6.

2. Related Works

In this section, we first briefly discuss the characteristics of data generated by massive sensor devices and review the IoT systems for managing diverse data. Then, we introduce the literatures focusing on edge cloud network architecture and utilization of AI technologies for efficient data management, and finally identify remaining challenges for horizontal IoT platform enabling cross-domain data fusion we focus in this paper.

2.1 Big Data and Cross-Domain Data Fusion

As stated in the Introduction, the proliferation of sensor devices and deployment of diverse sensing systems explosively increase the amount of data disparate in quality and value. S. Oteafy [7] notes that the big sensed data (BSD) potentially depletes communication resources and even makes data analytics unmanageable. That is, BSD management is a pressing issue. Lin [8] mentioned that the main objective of IoT is to interconnect various networks for efficient data collection, analysis, and management across heterogeneous networks. The authors advocated that a horizontal IoT platform enabling cross-domain data fusion becomes crucial (as in [2]) and smart cities is one of the most representative CPS/IoT applications. Celes [9] first listed a set of cross-domain data in urban environment (referred to as urban data), and then overviewed their advantages and limitations for crowd management. They showed the understanding of crowd situations based on urban data can bring many opportunities such as urban planning, intelligent transportation systems, and traffic optimization.

2.2 Network Architectures for BSD Management

Qiu [10] and Huru [11] focused on the network architectures and platforms to manage the BSD collected from diverse domain fields. The authors pointed out that horizontal data processing architecture that integrates cross-domain IoT data platforms becomes crucial for providing a variety of convenient services for our future. Qiu [10] proposed a layered approach in which all of BSD are transmitted to cloud servers by networking layer and processed there. Huru [11] proposed BigClue for data processing across multiple IoT domains. The BigClue is also a cloud-based data processing architecture that performs the complex processing demanded by cross-domain IoT data in the cloud, and makes decision.

The work in [2] introduced a new architecture employing fog/edge computing as a support of cloud computing. Since the fog/edge computing can act as a bridge between end devices and cloud server, the architecture has the potential to alleviate the burden of data processing and traffic congestion, and to deliver better delay performance, while increasing service resiliency and scalability. Elkheir [12] overviewed the available processing paths throughout the lifecycle in managing IoT data. However, the authors did not mention how to design the concrete system architecture. Moysiadis [13] surveyed ongoing research projects focusing on distributed fog/edge computing for IoT services. In this paper, the authors clarified that the storage capacity at each location can be determined by the volume of data from the devices with geographical proximity. Oteafy [14] focused on the fog computing architecture with the characteristics of lower access latency and limited geographical proximity as a means of coupling of services with local IoT components in user-centric contexts. However, the authors only presented many future directions along this line, but did not discuss how to achieve the convergence of communication and computing in the edge cloud IoT system for providing user-centric services.

While the above works mainly focused on the architecture of the edge cloud network, consideration of their heterogeneous characteristics such as computation capacity, caching capacity, and communication performance becomes essential for improving user QoE. Hao [15] proposed the Smart-Edge-CoCaCo algorithm that uses joint optimization of the wireless communication model, the collaborative filter caching model in edge cloud, and the computation offloading model. Zhou [16] extended the architecture for convergence of communication and computing, and proposed a heterogeneous communication and hierarchical computing network architecture, thereby improving capacity over conventional cloud-based IoT system. In order to meet users’ QoS requirements in edge and remote cloud environment, Liu [17] presented optimal multi-resource allocation policy for computing and bandwidth resources for IoT services. Furthermore, Cicconetti [18] proposed the cloud server-less distributed computing architecture (con-

sisting of edge servers only) and considered severe limitations in edge domain in terms of scalability, performance, and reliability, compared with the cloud domain. Wu [19] also employed the collaborative edge computing (server-less architecture), but focused on an important issue of establishing trustworthiness among all edge servers. To address this issue, the authors proposed a blockchain-powered framework, called BlockEdge that can build trustworthy edge-centric network and deliver trusted services.

2.3 Optimization Using AI Technology

Recently many researchers are paying attention to AI technology for optimizing not only communication procedures but also data processing required in the edge cloud network architecture. Karunaratne [20] discussed key machine-learning (ML) technologies and analyzed past efforts applying ML to solve various design and management tasks related to wireless mesh networks. Guo [21] handled task offloading for achieving efficient edge computing and mentioned that existing researches cannot deal with varying situations. To solve this issue, the authors utilized supervised decision tree based ML technology into task offloading at the edge for designing an intelligent task offloading scheme. Rodrigues [22] mentioned that “Modeling of edge cloud network with a variety of users, servers, and applications” involves inevitably many parameters for optimal configuration of communication, resource allocation, and so on. Therefore, the authors presented unsupervised learning approach to achieve near-optimal solution and provided helpful guidance which ML solutions can be applied to which problems. Finally, Chen [23] surveyed applications where state-of-art deep learning are used at the network edge, and described example applications including not only in-network caching as a network function but also IoT contents that need to be fused and processed together in the spatiotemporal manner. However, the authors did not clarify how to provide these applications in the edge cloud network architecture.

2.4 Cache Management on Edge Cloud Network

Several papers focused on edge caching in which edges with cache storages can solve several problems of edge cloud network architecture. Yao [24] overviewed the state-of-the-art edge cloud network and its advantages, and discussed how the location of edge caching impacts on the cache performances. Moreover, the authors divided the caching process into four functions: content request, exploration, delivery, and update, but mentioned that none of the existing studies takes the dynamic IoT contents fused by multi-source and/or variable IoT data into consideration. That is, how to design the caching strategies by incorporating the dynamic IoT contents still remains as one of important challenges. Sinky [25] also focused on in-network, content-centric caching approaches for smart cities. The information of network topology, content popularity, and users’ trajectory is assumed and utilized for efficient content caching and delivery, thereby

minimizing service disruption. However, other three functions (contents request, exploration, update) were not discussed. Pattar [26] mentioned that combining the IoT data can build dynamic IoT contents and reviewed state-of-the-art content search methods. The authors reviewed search methods in view of location, content, and spatiotemporal basis; however, none integrated all three attributes which can substantially facilitate content search in edge cloud network. The authors also mentioned that dynamic and real-time recognition and response to user queries becomes important to improve the QoE of users.

To the best of our knowledge, none of existing studies proposes a new information platform that can provide essential functions [24] for dynamic IoT contents fused by IoT data. This paper is the first concept paper of geolocation-centric information platform for dynamic IoT contents management that embraces essential functions, in the resilient manner.

3. Geolocation-Centric Information Platform (GCIP)

As stated earlier, some types of environmental and user behavioral data suitable for the cross-domain data fusion are generated and managed in the geographical proximity. Therefore, we assume that public organizations such as local governments (LGs) (e.g., municipal and prefectural offices) are responsible for collecting and managing these data, and contents providers (CPs) contracted with the LGs are responsible for producing STCs by fusing the cross-domain data obtained from LGs. That is, each of edge cloud can be built by the cooperation between LGs and CPs.

For example, some static environmental and personal data such as map, residential address, and social security information are strictly managed by LGs. On the other hand, more dynamic data such as temperature and user behavior information are collected to the cloud server to provide a specific service. If these dynamic data can be collected at the edge cloud serving a specific geographical area, we will be able to fuse these abundant cross-domain data, thereby producing new/diverse STCs. For example, the relationship between the discomfort index (DI) calculated from temperature and humidity and human traveling flow can be used for the estimation of wireless resource utilization.

As mentioned in Sect. 2, to utilize STC effectively, four essential functions consisting of STC production, STC discovery, STC delivery, and fault tolerance management should be provided in the resilient manner. Therefore, in this paper, we here propose a new information platform, geolocation-centric information platform (GCIP) with edge cloud for Spatio-Temporal Content (STC) management is as shown in Fig. 1. We first outline the concept of the proposed GCIP (shown in Fig. 2) and briefly describe its two main components: (1) infrastructure-based geographic hierarchy edge network (GHEN) and (2) adhoc-based STC retention system (STC-RS). Also provided is the description of adaptive use of these two components.

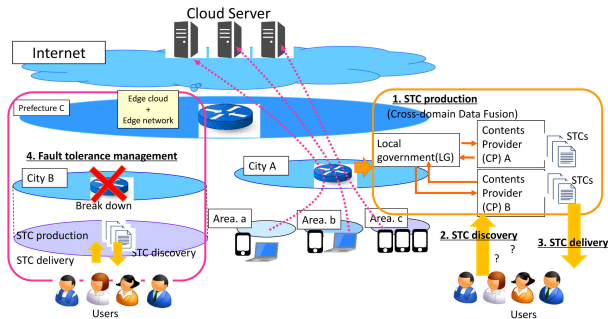


Fig. 1 Essential functions for resilient STC management on edge cloud.

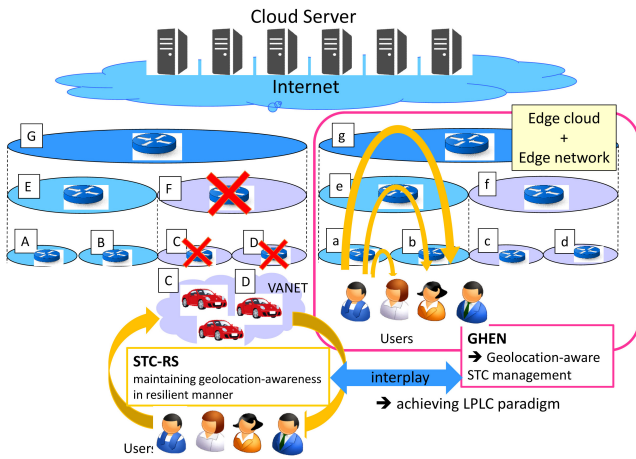


Fig. 2 Conceptual architecture of the GCIP.

3.1 Concept of the GCIP

Since STC strongly depends on the location and time where and when it is generated, we advocate that the most effective exploitation of STC could be to deliver it directly to the users who are at the location (local production for local consumption, LPLC), rather than serving it from remote cloud servers.

GCIP manages the interplay between GHEN and STC-RS for STC management. The GHEN is a hierarchical edge network handling variables in geographical proximity, while STC-RS is virtually built over multiple vehicles located in a certain region by forming a wireless network in the ad-hoc manner. The GHEN provides a network substrate supporting “geolocation-aware” STC management, whereas the STC-RS maintains the geolocation-awareness in a resilient manner even when the infrastructure fails.

As a result, our proposed GCIP can achieve consistent STC management (production, maintenance, and delivery), while maintaining not only geolocation-awareness but also resilient nature. Furthermore, as a secondary advantage, since GCIP can complete all the processing required for the STC management within the edge network, congestion in the core network can be mitigated.

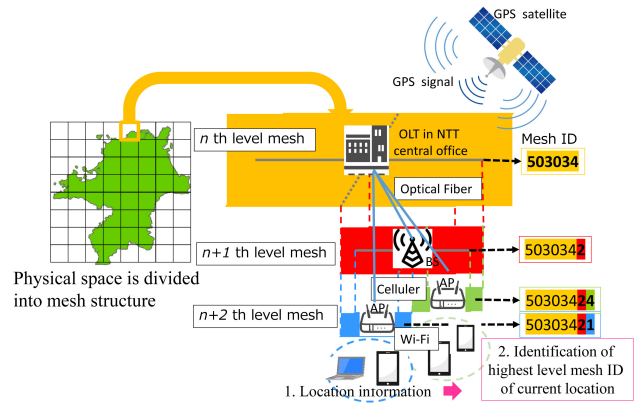


Fig. 3 Topology and allocated mesh IDs of GHEN.

3.2 Infrastructure-Based Geographic Hierarchy Edge Network (GHEN)

A geographical space is virtually divided into meshes based on the latitude and meridians lines and the meshes is organized in a hierarchical structure as shown in Fig. 3. One 1st level mesh is 80 km by 80 km square area and one 2nd level mesh is 10 km by 10 km square area; that is, one 1st level mesh is equally divided into 64 2nd level meshes. For the n th level for ($3 \leq n \leq 10$), we define that one n th level mesh is divided into four ($n + 1$)th level meshes.

A unique number, called mesh ID of variable length is allocated to each of meshes: 1st level mesh is given a 4-digits decimal ID and additional 2 digits for 2nd level meshes. Note that in Japan, geographical areas and those IDs for 1st and 2nd level meshes are pre-allocated by NTT DoCoMo Open iArea [27][†]. The ID length allocated to higher than 3rd level meshes increases in proportion to the increase in the level. Figure 3 illustrates an example ID allocation. Assuming the area covered by one Wi-Fi AP 50 m by 50 m square area, we define the minimum (10th level) mesh size as 39 m by 39m square area. This mesh ID allows us to flexibly identify the geographical spaces in handling STCs.

To identify the mesh ID, any devices in GHEN need to acquire its geolocation information. Widely implemented GPS in smartphone and network devices such as cellular Base Station (BS) and Wi-Fi AP conveniently provide geolocation information. Even without GPS, inexpensive sensor devices can obtain approximate geolocation information from their APs and BSs of the infrastructure network.

However, in practical environments, some network facilities are forced to be located at non-optimal area due to the limitation of space availability: AP in home, cellular BS, and OLT (Optical Line Terminal) in a NTT central office. As a result, the topology of the GHEN inherently forms an irregular mesh as shown in Fig. 3. Also, as a large number of

[†] Although Open iArea is here employed as just one example of grid reference system, we can use the grid code defined by any kinds of reference systems including JIS X0410 (Japan), MGRS (USA), European Grid [28] for the GHEN.

APs are already deployed especially in the urban area, several APs can be accommodated within the minimum mesh area (10th level mesh).

3.3 Adhoc-Based STC Retention System (STC-RS)

As stated in Sect. 3.1, the STC-RS allows us to maintain the geolocation-awareness in a resilient manner, even when infrastructure network fails. To achieve this, large transmission bandwidth, large storage, and high-performance CPU are required as in the edge cloud. A virtual edge cloud is established over the VANET, thereby maintaining functions of STC management even when the GHEN becomes inactive due to a variety of network problems.

Modern vehicles (e.g., smart cars) have three remarkable features. First, data can be collected by and analyzed within individual vehicles owing to significant in-vehicle storage, battery power, and high-level computational resources in the near future. Second, emerging vehicle-to-everything (V2X) communication can provide high transmission capacity via such wireless standards as IEEE DSRC/WAVE and 3GPP C-V2X (Cellular V2X). Third, ubiquitous presence of highly mobile vehicles operating all over the world can function as a substrate layer over which efficient data collection and dissemination can be provided.

In this study, we employ user's neighboring vehicles as vehicular edge clouds for STC management, where each vehicle acts as an edge cloud. If the STCs are replicated and managed in multiple vehicles existing in the geographical proximity, users can obtain their desired STCs from one of the neighboring vehicles even when some vehicles move away and/or break down, not to mention the failure of the GHEN. As a result, the STC-RS achieves the LPLC paradigm for STC management in the resilient manner.

3.4 Interaction of GHEN and STC-RS

Basic concept of the hybrid system consisting of GHEN and STC-RS is already described in our prior work [29]. The cooperation between GHEN and STC-RS is critical if GHEN fails. If GHEN fails, STC-RS should first consider the geographical area of GHEN. For example, when a user moves from the failed area to the neighboring mesh area, the handover of STC management from STC-RS to GHEN should be performed according to the user mobility.

Since the information of vehicles' mobility and density in the wide area is available by the support of the GHEN, not only the estimation of the status of the STC-RS but also the preparation of the handover process of the STC management described above can be performed effectively.

4. Essential Functions and Technical Issues of the GCIP

In this section, we first clarify the essential functions, and then discuss technical issues with the proposed GCIP, which

engender main research items for GHEN and STC-RS.

4.1 Essential Functions

- STC production:** Integration of environmental data and user behavioral data in a certain geographical proximity can produce diverse STCs which have been difficult to realize so far. However, since the data are gathered into cloud servers, the data collection at the edge network beyond the border of network operators needs to be negotiated among relevant network operators. We assume here that the operators agreed already with data sharing under limited conditions of geographical proximity to provide diverse STCs for users. Furthermore, user's consent should be obtained in advance. Since edge servers for data management and mesh routers are assumed to be isolatedly operated by LGs and Telecom companies, edge router should replicate the data and transfer the replicated data to the edge server, while transmitting original data to the cloud server. As a result, the data transmitted from certain geographical areas are collected at the edge server managed by LGs. In parallel, to produce appropriate STCs flexibly, how the CP retrieves the necessary data from the edge server managed by LGs should be carefully planned.
- STC discovery:** The data collected from massive IoT devices will experience spatio-temporal change in view of the amount and generation rate. As a result, the STCs produced by the CPs by the cross-domain data fusion is also inherently spatio-temporal. In such a case, users who want to get a STC on the edge server cannot directly discover which CP has the desired one. Therefore, methods for STC discovery should be properly designed.
- STC delivery:** Since users may search desired STCs from anywhere in the Internet, the associated locations can be widely different. If a remote user wants to get some STC for a specific geographical area, the granularity of the STC needs to be dynamically modified according to its privacy policy that is differential privacy. After discovering the desired STCs, an effective delivery method should be selected from among multiple candidates in response to both of the user location and the demands for the STCs such as time constraints and confidentiality.
- Fault tolerance management:** Resilience is closely related to reliability of networks when a subset of edge clouds becomes inactive. GCIP service disruption may happen due to edge network failures, temporary hardware failures, maintenance, power outage, access imbalance congestion, etc. Therefore, alternative methods that can maintain all of the STC management functions (production, discovery, delivery) should be considered even when none of edge clouds are available. We are tackling how to secure fault resilience management in edge cloud network through NSF/NICT

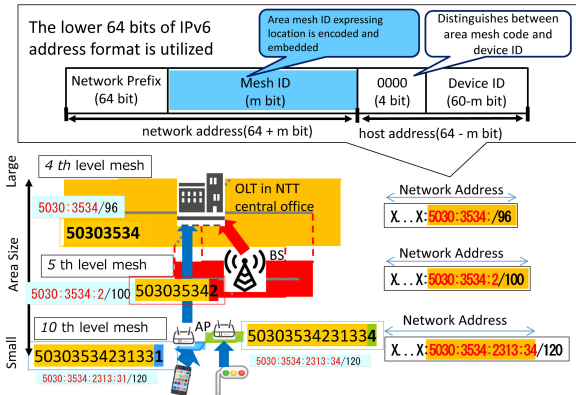


Fig. 4 Physical location-aware communication (PLAC) method.

JUNO2 project [30].

4.2 Research Items in GHEN

4.2.1 Geolocation-Aware Data Collection

In order to collect geolocation aware data, we introduced in Sect. 3 the mesh ID, so that all network devices such as mesh router and terminals for GHEN can identify their own geolocation and corresponding mesh IDs to handle all of data containing the same mesh ID. We present a new data communication method that can consider geolocation, called physical location-aware communication (PLAC) method.

For smooth deployment of the new PLAC method, we adopt the geolocation aware IPv6 compatible (GIP) address format [31], which is compatible with the current IPv6. The GIP does not modify the network prefix (the upper 64 bits) as show in Fig. 4. Instead, a mesh ID described in Sect. 4.2 is embedded in the lower 64 bits of IPv6 address because the lower 64 bits can be freely determined while avoiding address duplication (as in the stateless autoconfiguration).

Specifically, a mesh ID is placed in the beginning of the lower 64 bits and used as a part of network address. Since the network address length matches the size of physical region, the PLAC is achieved by IP routing on the basis of longest match by using the extended network address (prefix + mesh ID). This means that by choosing either IP or GIP address, the users can indicate their willingness to agree or not the geolocation aware data collection at mesh router in the GHEN. Thus, the use of the GIP address by a user indicates her consent to geolocation aware data collection[†].

4.2.2 Publish/Subscribe-Based Networked Data Preprocessing for STC Production

As stated in Sect. 3, we assume that local governments

[†]We assume that users need to choose GIP address on a per-application basis when they agree with geolocation aware data collection at mesh routers in the GHEN. The actual operating procedures are supposed to be like a means of selecting an access network such as Wi-Fi or LTE on smartphone.

(LGs) such as municipal and prefectural offices are responsible for collecting and managing these data, and content providers (CPs) contracted with the LGs are responsible for producing STCs by fusing the cross-domain data obtained from LGs. To achieve this, we consider that a data storage (DS) server and data fusion (DF) server(s) are deployed in each mesh area, operated by LGs and CPs respectively. The former is operated by LGs and the latter is by CPs. Since the interplay of these servers yields the diverse STCs, the communication method between the DS server and the DF server should be defined. The Publish/Subscribe model will be used for this communication.

In this model, the mesh router publishes the collected data to the DS server and the DS server stores/aggregates the published data. Each of the DF servers, as the “subscriber”, requests the stored information from the DS server. Data mining will be performed on the DF server to produce useful STCs by exploiting an appropriate AI technology.

In general, intensive preprocessing including anonymous processing, Fourier analysis, labeling, and object extraction is required before AI processing, but many processing functions can be made common because of their wide range of use cases. Therefore, we will consider a networked preprocessing method in which multiple DF servers with different functions execute the preprocessing in order. Since efficient preprocessing order can be designed by considering both the functions each DF server maintains and the network load, the flexible functions of SDN (Software-Defined-Networking) technology is utilized for obtaining the information. Note that since we here focus on the edge network operated by LGs and CPs, the scalability problem in SDN can be mitigated.

4.2.3 User/CP Requirement Matching-Based STC Search

Since users and sensor devices are numerous and diverse, their data transmission timing, intervals, and the amount are also significantly different. Therefore, the retrieved data from the DS server will change depending on not only “time” but also “location”. Moreover, the types of processing may range from simple computations such as finding the maximum/minimum or mean value over a set of sensed data (e.g., movement speed and temperature) to more complex data aggregation, spatial/temporal correlation or filtering operations on the raw data. As a result, the STCs produced by the DF server will also exhibit the spatio-temporal characteristics.

The popularity of STCs requested by users also varies spatio-temporally. Therefore, a search techniques tailored to both location and contents are necessary. Although wide variety of search techniques exist [26], studies still lack addressing the spatio-temporal characteristics in terms of the STCs and users’ request (popularity). In the proposed GCIP, since the DS server can collect the statistical information of both users’ and CPs’ requests, we proposed a new content discovery method that evaluates the relevancy between topics specified user requests and topics representing IoT data

used for creating STCs, called matching, and presents the candidates for the desired STCs based on the relevancy [32].

4.2.4 Geolocation-Aware STC Delivery on GHEN

In the proposed GCIP, every IoT data or STCs need to be delivered through the mesh structure; that is, the delivery route to the location of designated destination is automatically determined by following the mesh structure in which every data must go upward through router(s) on higher level(s) and again go downward through router(s) on lower level(s). This means that not only the amount of data traffic increases but also the area suffered from the traffic is wider, in proportion to the extension of the length of delivery route.

Even if only the summarized information is sufficient for distant users, transmitting detailed information may pose privacy concern. The private information accessible for local users can be visible to distant users as well. To solve this issue, we focus on the gap between transmitted granularity and required granularity of data, and propose a new data delivery method in GCIP that can take the physical distance into account.

According to the mesh architecture presented in Sect. 4.2.1, the number of packets that routers in the network process increases in accordance with the physical distance between the source and destination. We rather exploit this to control data granularity. Specifically, we proposed an in-network processing mechanism on GCIP, which changes information granularity when a communication data passes each router [33]. In this mechanism, we put a same function of data processing into every router and that function is executed for communication passing from lower-level mesh to higher-level mesh. As the number of routers increases, the information granularity becomes coarse due to the increase of the number of data processing. On the other hand, when the data is transmitted to a very near location (e.g. within the same mesh), data processing never happens.

4.3 Research Items in STC-RS

The STC-RS allows us to maintain the geolocation-awareness in a resilient manner, even when infrastructure network (GHEN) fails.

4.3.1 STC Production in High Mobility Environment

Although STC-RS is virtually built on a VANET to locally maintain all the functions of STC management provided by the GHEN, the VANET has significantly different properties compared with the GHEN. For example, vehicles inherently have high mobility and their density is time dependent. As a result, the topology of the VANET envisioned in this system becomes dynamic. Thus, the availability of the functions for data analysis and/or processing for STC production will also be time-varying. Therefore, how to produce the STC by using the available functions at any point of time should be considered.

4.3.2 STC Distribution in High Mobility Environment

As discussed in Sects. 3.4 and 4.1, to guarantee the GHEN's fault-tolerance and achieve physical location-based delivery of STCs, we proposed the STC-RS using vehicles where users in the certain area can receive STC from a vehicle spreading a data uniformly. However, since the STCs can be produced over the VANET, the STC retention will become extremely difficult due to the vehicles' high mobility and time-varying VANET topology. Therefore, we proposed the data transmission control method (DTCM) for achieving that each vehicle periodically distributes STCs by wireless communication within its specific area (defined as the target area) whose geographical size is to be determined by the mesh structure of the GHEN [34]. We defined the coverage rate (CR) as a target metric. The CR is represented by $\frac{\text{Total area STC can be received}}{\text{Total area}}$. Furthermore, the reduction of number of data transmissions is also our objective for the effective use of wireless resources for the STC-RS.

The process of the DTCM begins when the vehicle receives the STC from the STC producer (e.g. DF server(s) on GHEN). Each vehicle sets data transmission interval d , which is notified by the STC producer whenever receiving initial data (STC)[†]. Here, the subscript i indicates a unique vehicle ID, $i \in V$, where V is the set of all vehicles, and the subscript t indicates the sequence number of data transmission cycles (i.e., the number of d) after the first data reception. First, the vehicle sets a random backoff time s ($< d$) to avoid packet collisions. After s has elapsed, the vehicle sets the transmission probability in the following procedure to control the number of packet transmissions while maintaining coverage. Each vehicle in the target area estimates the number of neighboring vehicles $n_{(i,t-1)}$ from the beacons transmitted by vehicles every cycle t , which has to be set smaller than d . Next, when the number of neighboring vehicles is four or more, the vehicle's transmission range has the potential to be completely covered by that of all neighboring vehicles. For example, when the neighboring four vehicles are located to a vehicle's north, south, west, and east (the ideal arrangement), the vehicle's transmission coverage area is already completely enclosed by the neighboring vehicles. Therefore, if $n_{(i,t-1)} < 4$, the vehicles set transmission probability $p_{(i,t)} = 1$ and always send the STC packet since it is difficult to cover the entire target area with just the neighboring vehicles. On the other hand, if $n_{(i,t-1)} \geq 4$, the vehicle determines the transmission probability based on the number of STC packet transmissions by neighboring vehicles to avoid packet collisions. In order to calculate the estimated number of STC packet transmissions $m_{(i,t)}$ by the neighboring vehicles in the t -th cycle, the vehicle uses the number of received STC packets $l_{(i,t-1)}$ from the neighboring vehicles in the last ($t-1$ -th) cycle. $m_{(i,t)}$ is calculated by the following equation:

[†]Note that we here assume a STC can be included in one packet.

$$m_{(i,t)} = \alpha * l_{(i,t-1)} + (1 - \alpha) * m_{(i,t-1)} \quad (1)$$

where α indicates the moving average coefficient. Finally, the vehicle determines $p_{(i,t)}$ based on the $m_{(i,t)}$ as follows:

$$p_{(i,t)} = \begin{cases} p_{(i,t-1)} + \frac{\beta - l_{(i,t-1)}}{n_{(i,t-1)} + 1} & (0 < m_{(i,t)} < \beta) \\ p_{(i,t-1)} & (m_{(i,t)} = \beta) \\ p_{(i,t-1)} - \frac{l_{(i,t-1)} - \beta}{n_{(i,t-1)} + 1} & (m_{(i,t)} > \beta) \end{cases} \quad (2)$$

where β is the target number of data transmissions around a vehicle.

By determining the transmission probability of STC by the DTCM, high delivery rate can be achieved while avoiding waste of wireless resources. Moreover, we have made several extensions for simultaneous multiple STCs retention [35] and secure communication with other vehicles [36] [37]. Especially, in high mobility environment, since the vehicles move out of the target area and move into the new target area, we have proposed a method for quick STC distribution and deletion [38] to limit the retention area of STC. However, a new deletion method of the STC needs to be developed in the consideration of vehicle's movement and the STC's target area.

5. Experiments

In this section, we have conducted the experiments to show the efficacy of (i) STC production on the GHEN and (ii) STC distribution over the VANET.

5.1 STC Production on the GHEN.

The preliminary experiments were conducted on real campus IPv6 network [39]. In this experiment, we examined whether the GHEN can collect the IoT data by exploiting PLAC method, even when the data are generated in adjacent proximity but transmitted from different 10th level meshes (i.e., different subnets/prefixes). As shown in Fig. 5, each of 10th level mesh networks has corresponding mesh router (R10.0 and R10.1) and an access network. Five end devices (D1.1, D1.2, D1.3, D2.1, D2.2) are developed by using Raspberry Pi and equipped with different types of sensors. These end devices are connected via Ethernet and transmit sensed data periodically (every 5 minutes) throughout the experiment.

For the second experiment, we examined the feasibility of STC production on the GHEN by fusing the sensed data collected in the geographical proximity. We consider the discomfort index (DI) as a simple example of the STC. Here, we assume that some of sensors in the geographical proximity send the temperature information to a specific cloud server for work smart, while other sensors send the humidity data to a different cloud server for smart cities. Then, the DI is calculated from these two cross-domain data as " $T - (0.55 - 0.0055RH) \times (T - 14.5)$ " [40]. Note that T indicates the mean value of air temperature and RH indicates the 5 minutes average of relative humidity because the

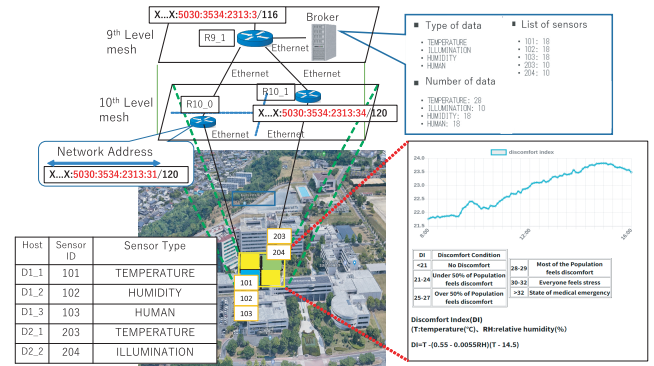


Fig. 5 Demonstration for IoT data collection.

sensor devices transmit their average data every 5 minutes.

The PLAC method allows three sensor devices (D1.1, D1.2, D1.3) deployed in the mesh with ID 50303410 to forward their sensed data to R9.1 via their mesh router (R10.0). Similarly, sensed data from D2.1 and D2.2 in a mesh with ID 50303411 are forwarded to R9.1 via their mesh router (R10.1). Note that these 10th level meshes have different network prefixes, i.e., different subnets. However, since the R9.1 is located at the same (9th) mesh network, if the data storage (DS) and data fusion (DF) servers are also located at the same 9th mesh network, all of the sensed data can be collected from the mesh router. We here use Apache Kafka, which provides publish-subscribe based messaging system [41], for communication between end devices and DF servers managing STCs. Since a broker is necessary for mediation between producers and consumers, we deployed a broker on the 9th mesh network. For simplicity, the broker functions as the DS server and the DF servers, and typical Web API is used for indicating the STC produced in the broker.

Figure 5 also shows the STC generated at the broker. Fig. 5 illustrates not only a geographical area where the STC was produced but also a time series variation of DI value. Since the GIP address includes a mesh ID, the broker can roughly identify the geographical area of end devices by analyzing the IPv6 header of the packets received from the end devices. Moreover, the broker can store the published data, and thus the change in the DI value can naturally be shown. Through these experiments, we demonstrated that the proposed GHEN can produce STCs by using the PLAC method.

5.2 STC Distribution over the VANET (STC-RS)

We evaluated our proposed method using the Veins combined network simulator OMNeT++ and the road traffic simulator SUMO. As shown in Fig. 6, a road model on a grid of 2 km square with 200 m distance between each road is used as the simulation area, and vehicles drive randomly on this road at a 40 km/h. The communication range of vehicles, the beacon transmission interval, the data transmission interval d , α , and β are set to 300 m, 1 s, 5 s, 0.5, and 4,

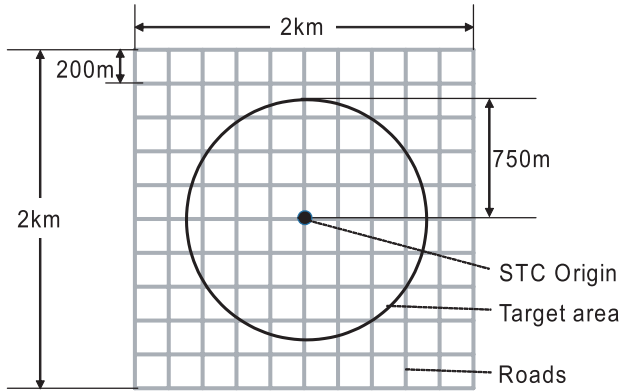


Fig. 6 Simulation topology.

respectively. These parameters were set to appropriate values for proposed method based on the evaluation of previous works [34]. One STC is transmitted from the center of the target area (STC origin) at the start of the simulation and is retained by the vehicle for 100 s within a 750 m radius of the target area. Note that we here set the radius of the target area to approximately three times (hops) of that of the communication range in order to show the effectiveness of the proposed retention method on relatively large area. Furthermore, to examine how the change in the node density impacts on the retention performance, the number of vehicles is varied from 75 to 300.

We compared the proposed method with the naive method (always with $p_{(i,t)}$ of 1), which can maintain high coverage but not taking into account the consumption of wireless resource. Figures 7 and 8 show the CR and the transmission reduction rate (TRR), when the number of vehicles is varied. Note that, the TRR is calculated by $“(1 - \frac{\text{Total TX num. of the proposed method}}{\text{Total TX num. of the naive method}}) \times 100”$. In terms of CR, the proposed method achieves more than 99% but is slightly lower than the naive method. On the other hand, we confirmed that the TRR of the proposed method is approximately 70% lower than that of the naive method in high node density. The results show that the proposed method can maintain a high CR while significantly reducing the number of data transmissions.

6. Conclusion

In this paper, we advocate that “local production for local consumption (LPLC) paradigm” is an innovative approach in cross-domain data fusion and propose the geolocation-centric information platform (GCIP) that can produce, maintain, and deliver new/diverse spatio-temporal content (STC).

In the GCIP, we assumed that local governments (LGs) are responsible for collecting and managing data, and contents providers (CPs) contracted with the LGs are responsible for producing STCs by fusing the cross-domain data obtained from LGs. CPs are also responsible for the development of the required functions for resilient STC man-

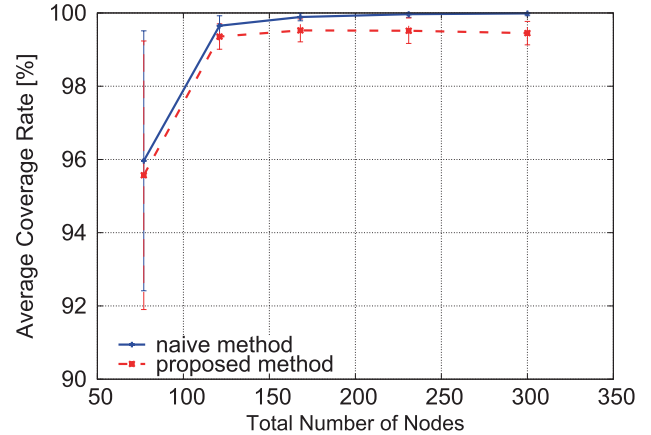


Fig. 7 The CR vs. the total number of nodes (vehicles).

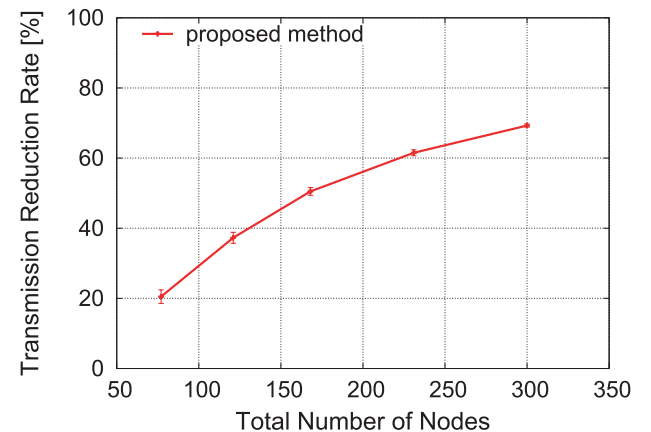


Fig. 8 The TRR vs. the total number of nodes (vehicles).

agement in edge cloud. By integrating VANET-based STCRS with the infrastructure-based GHEN, we provide much needed resilience to the GCIP.

Technical issues of GCIP have been discussed with its two cooperating components: GHEN, the geolocation-based hierarchical mesh and resilient VANET-based STCRS. Then, we showed the feasibility of the proposed GHEN via a POC system, which implemented and demonstrated effective data fusion of raw data obtained from different networks within GHEN by using the PLAC method. Practical experiments have been conducted on campus IPv6 network. Furthermore, we also showed the effectiveness of the STC distribution by the proposed STC-RS through simulation experiments. Although the POCs demonstrated in this paper were very limited, we have already started several researches on other technical issues described in Sect. 5, such as Publish/Subscribe-based networked data preprocessing, User/CP requirement matching-based STC search, STC production/distribution in high mobility environment, and the way of GHEN and STC-RS interplay. We plan to report performance of the proposed GCIP in the near future.

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