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Quasi-holography computational model for urban computing

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ABSTRACT

Vast amounts of data are produced with the development of smart cities and urban computing technologies. The data is often captured from multiple sensors, with heterogeneous structures and highly decentralized connections. Integrated data representation and smart computational models are required for more complex tasks in urban computing. We dwell deeply on two fundamental questions — *can we provide an integrated data representation for the whole cyber–physical–social system? And, can we provide an integrated framework to choose the appropriate data for understanding a specific urban event?* A holography data representation and the quasi-holography computational model have been proposed to address these problems. We describe case studies using the quasi-holography computational model, and discuss further problems to solve regarding our model.

1. Introduction

Intelligent devices, simulations and communications in modern cities produce massive data: GPS signals, personal images, atmosphere, and 3D buildings are all examples. These data reflect urban evolution in physical, social and cyber spaces, playing a significant role in urban management, security, and activities. However, these data are often captured by different sensors located in disparate places, and may have different inherent data structures. The multi-source, highly decentralized and heterogeneous attributes of urban data make them challenging to process, fuse and analyze. An appropriate representation and computational model for processing and mining urban data is necessary, and even critical for complex applications (Lazer et al., 2009; Cook, 2012).

A cyber–physical–social system (CPSS) is proposed to describe an ideal infrastructure which enables urban data computation, communication and applications (De et al., 2017) in cyber, physical and social space. The fundamental idea of this conceptual infrastructure is to integrate the multidimensional and multidisciplinary nature of data sources that cross the three subspaces in CPSS (Sheth et al., 2013; Cassandras, 2016; De et al., 2017). Consequently, data are the most important constitutes of CPSS, which can be organized and categorized to each subspace. The physical space encompasses entity data, such as buildings and towers. Data in the social space are recorded from either visual sensing or digital activities among social network, such as mobile phone records and online messages. The cyber space contains virtual information based on physical and social space, such as POIs. Therefore, data from different subspaces are heterogeneous, highly dispersed, and of low relevance. When analyzing a specific urban event, the data may be redundant on one hand, but insufficient on the other. This inspires us to contemplate two significant questions: *can we provide an integrated data representation for the entire cyber–physical–social system? Furthermore, can we provide an integrated framework to select the appropriate data to understand a specific urban event?*

Here we propose a unified temporal and spatial framework for representing the heterogeneous, highly dispersed, and low-relevant urban data, termed *holography data representation*. It encompasses a holistic representation of three layers (e.g., data, semantics and knowledge) based on the cyber–physical–social system. *Holography data representation* is viewed as an ideal model for the entirety of space, which unifies all the data, semantic correlations among data, and high-level knowledge for solving urban events. To analyze a specific event and focus on its dynamic changes, we further provide a quasi-holography computational model based on *holography data representation*. The computational model takes a target event and quasi-holography data as input, maps the different scales of data to depict the event, resulting in sufficient data for the event. This computational model helps people evaluate and track events, and even plant new sensors for self-updating the compactness of data for specific computing tasks.

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We illustrate the *holography data representation* and the *quasi-holography computational model* in detail with cases and examples, showing their great compatibility and extendability in event-driven urban computing tasks.

In summary, the main contributions of our study are as the following:

- a conceptual holography data representation for unifying data sources, their inherent semantics and latent knowledge in urban computing.
- a quasi-holography computational model to address the problem of sampling quasi-holography data for target events.
- how to leverage our model to analyze urban computing cases.
- promising open problems based on the quasi-holography computational model.

2. Background work

2.1. Cyber–physical–social system

With the rapid development of Internet Plus, big data, Internet of things and other related technologies, information and physical systems have been further integrated. In addition, the development of various emerging mobile services and the popularity of mobile terminal equipment has made humans the most sensitive "social sens". In this case, the network and human society are seamlessly combined, forming a more complex integration of people, things and information all in one system, which is the cyber–physical–social system (CPSS) (De et al., 2017).

Smart city is a typical CPSS, where a large amount of physical space–time data can be obtained by detecting physical phenomena through distributed sensor networks, as citizens provide human-related social data through wearable sensors, smartphones, and online social networks. The vision of the CPSS provides a unified idea to extract useful information and knowledge from this data, in turn providing intelligent applications and services for governments and citizens (Sheth et al., 2013; Cassandras, 2016).

However, it has not been discussed on how to choose appropriate data or evaluate whether the data is sufficient to understand a specific urban event. It intrigues us to search for a holistic data representation for data and their relationships within society.

2.2. Urban big data

With the development of digital city projects, more and more cities in the world have built a better urban information infrastructure, providing a flood of urban big data. Urban big data consists mainly of data captured from fixed and mobile sensor networks (e.g., data captured through the digitalization of physical entity: cities, transportation, medicine, etc.) and human contributed e data (e.g., E-mail, instant messages, etc.), which can provide (near) real-time sensing of the urban environment and broad field coverage (De et al., 2017).

These data describe all aspects of a city's real physical environment and social life from multiple dimensions, forming a virtual mirror parallel to the real world. Urban big data has obvious "4V" features: massive data volumes (Volume), diverse data types (Variety), real-time dynamic data (Velocity), and huge data values (Value). It is important for a smart city to extract knowledge and intelligence from these data through data mining and correlation analysis.

2.3. Urban computing

In the urban computing community, many methods have been proposed to capture, integrate and analyze heterogeneous data sources in urban spaces (Paulos and Goodman, 2004; Varshney, 2007; Zheng et al., 2014; Tang et al., 2017; Zhao et al., 2018; Silva et al., 2019), providing reasonable approaches to implement conceptual cyber–physical–social infrastructure and improve city intelligence.

Continuous urbanization processes, however, pose challenging problems against the development and living quality of urban residents. Urban computing is proposed to solve these problems and improve the intelligence of modern cities. The term "urban computing" was first proposed by Paulos and Goodman (2004) and Paulos et al. (2004). Following their work, Zheng et al. (2014) presented a more thorough definition for urban computing, considering it as a process of acquisition, integration and analysis of tremendous heterogeneous urban data. Urban computing covers problems in smart cities, such as traffic congestion, healthcare monitoring (Varshney, 2007; Miotto et al., 2016), environment monitoring (Ong et al., 2016; Yi et al., 2018; Qi et al., 2018), and public safety (Anagnostopoulos et al., 2008; Liu et al., 2016; Tang et al., 2017).

In urban computing, flow analysis is a crucial problem that mainly focuses on the management of traffic or crowds mobility. The key step of urban flow management is to understand and capture multiple-sources of data (Zhao et al., 2017) from different physical urban sensors. To extract urban flow information from webcam images, Zhang et al. (2017a,b) introduced the methodology to count the number of cars from raw noisy data, with consideration of challenging factors such as low resolution and high occlusion. Zhao et al. (2018) further extended this method for different kinds of image data sources captured from different sensors. There are other useful and effective applications in urban computing. However, most of the methods are task oriented. Limited attention has been paid to the integration of data representation and high-level computational model.

3. Model conceptualization

In this section, we introduce concepts and definitions to address the problem of measuring data completeness, in analyzing a specific urban computing event. On the basis of our newly proposed (quasi-) holography data representation, we will introduce an event-driven quasi-holography computational model, accompanied by thorough constituents and examples in urban computing.

3.1. Holography data representation

Data (e.g., geo-spatial coordinates, surveillance videos, 3D models and mobile phone signals) in urban computing are often decentralized, heterogeneous and redundant, making it difficult to consolidate them for urban event analysis. We propose a *holography data representation* to unify diverse data sources and their relationships.

Holography data representation is defined as an integrated data framework based on temporal $\boldsymbol{\tau}$ and spatial $\boldsymbol{\sigma}$ information for unifying data sources and their correlations in the entire world. The *holography data representation* is composed of three basic layers: the data source layer, the semantics layer, and the knowledge layer, illustrated in Fig. 1. Ideally, the representation provides a way to build connections for different types of data to further help humans explore knowledge hidden within data. This conceptualization can be formulated as the equation below:

$$H(\boldsymbol{\tau},\boldsymbol{\sigma}) = H_d(\boldsymbol{\tau},\boldsymbol{\sigma}) + H_s(\boldsymbol{\tau},\boldsymbol{\sigma}) + H_k(\boldsymbol{\tau},\boldsymbol{\sigma}) \quad (1)$$

Fig. 1. An illustration of the holography data representation.

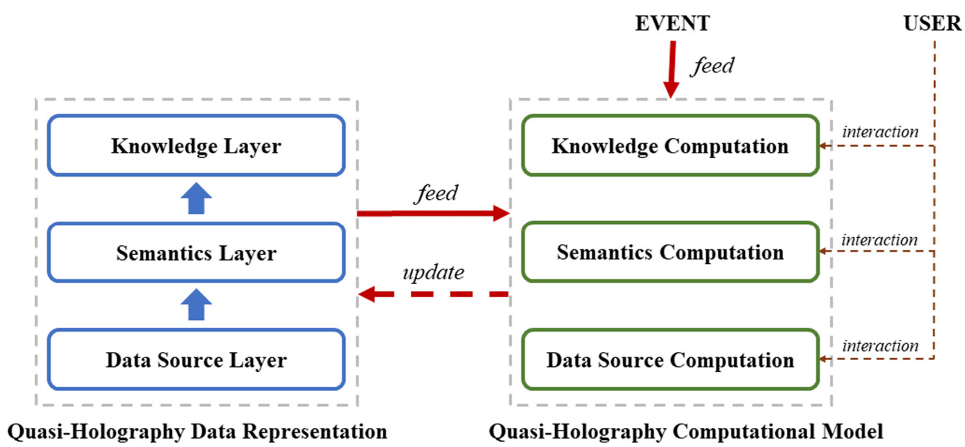

Fig. 2. An illustration of the quasi-holography data representation and quasi-holography computational model.

In the above formulation, H_d, H_s, and H_k depict the three fundamental layers. Data sources can be represented and registered according to their temporal and spatial information in a hierarchical way, while semantic correlations among data sources and corresponding latent knowledge are addressed as well. The three fundamental data layers will be further explained below.

Data source layer aims to ensure the integrality of data sources, which is constructed based on the concept of the CPSS. We categorize data sources to the cyber, physical and social spaces of CPSS. Thus, H_d can be further defined as the formulation below:

$$H_d(\boldsymbol{\tau},\boldsymbol{\sigma}) = H_d^p(\boldsymbol{\tau},\boldsymbol{\sigma}) + H_d^c(\boldsymbol{\tau},\boldsymbol{\sigma}) + H_d^s(\boldsymbol{\tau},\boldsymbol{\sigma}) \tag{2}$$

In this formulation, H_d^p represents entities in the physical subspace, such as buildings, trains and signal base stations. H_d^s represents data from the social network, such as instant messages, microblog, and personal information from wearable sensors. H_d^c indicates virtual information based on physical and social space, such as GPS, a satellite image or super-computing simulation data.

Semantics layer is a higher level computation based on the data source layer, composed of typical data processing and data fusion schemes. Our *holography data representation* on this layer, denoted as $H_s(\boldsymbol{\tau},\boldsymbol{\sigma})$, is able to infer common semantic embeddings based on the multi-model heterogeneous data, maximizing the intelligence of data processing and fusion. As an example, people can build efficient temporal–spatial correlations for multi-view surveillance videos, which can track a target in 3D space.

Knowledge layer aims to reason understandable knowledge from existing data sources and their semantic correlations. Ideally, the *holography data representation* on this layer can cover all the effective and useful knowledge reasoned from the whole data space. Imaging a thief were to escape with his goods, surveillance videos could record his actions, which would be further matched with his private ID information from the national security system. Based on thorough data sources, we can infer higher knowledge, such as his escaping velocity, his next station and even his reasons to steal. This knowledge layer can be denoted as $H_k(\boldsymbol{\tau},\boldsymbol{\sigma})$.

3.2. Quasi-holography computational model

Our *holography data representation* is an ideal framework with a complete expression of tremendous urban data. However, in most realistic cases, it is impossible and unnecessary to provide all the data for urban computing tasks. Suppose we focus on a stampede accident, data sources that are spatially far away from the accident are not necessary to represent the event. Consequently, we define the concept of ***quasi-holography data representation*** as a subset of the ideal *holography data representation*, encompassed with event-dependent data sources and their correlations. See the left side of Fig. 2.

Usually, quasi-holography data is accessible to people to some extent. For example, in a stampede accident, it is possible to acquire GPS signals and human trajectories inside the stampede region. It is unclear whether the data is sufficient to depict the

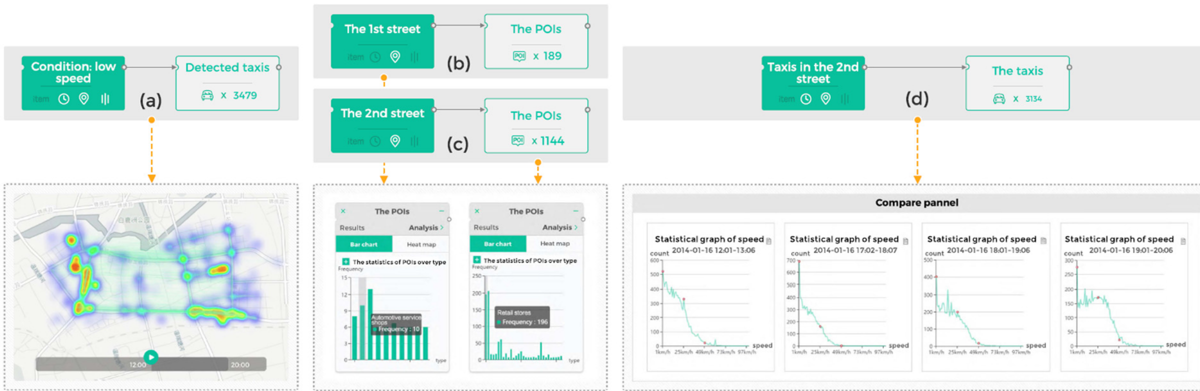

Fig. 3. The visualization interface (Chen et al., 2017) of our case study I.

urban event, or how much data is required for analysis. A computational model to measure the sufficiency of a quasi-holography dataset is significant to represent the dynamic urban event.

To measure the sufficiency of a quasi-holography dataset, we propose a *quasi-holography computational model*. In our vision, the *quasi-holography computational model* takes an event and a set of quasi-holography data as input, to return a new quasi-holography data representation just enough to analyze the event and suggest solutions. With this computational model, urban data sources and their correlations can be dynamically updated, computed and evolved. Interactions from users can be integrated to strengthen the accuracy and improve intelligence of the computational model. The whole process is depicted in Fig. 2. We can also depict the computational model with the equation below:

$$\begin{cases} \Delta^i = f(\hat{H}^i(\boldsymbol{\tau}, \boldsymbol{\sigma}), \boldsymbol{e}), \\ \hat{H}^{i+1}(\boldsymbol{\tau}, \boldsymbol{\sigma}) = \hat{H}^i(\boldsymbol{\tau}, \boldsymbol{\sigma}) + \Delta^i, \end{cases} \tag{3}$$

In this formulation, f depicts our *quasi-holography computational model*. Δ^i is the ith feedback of model f, which could be either positive or negative. If Δ^i is negative, it means that the current data sources are redundant for expressing an event; if positive, more data sources are required for the event. $\hat{H}^i$ depicts the ith iterative quasi-holography data representation. $\boldsymbol{e}$ denotes an input event; in our model, we refer to it as the temporal and spatial resolution of an urban event, or *event granularity*.

Event granularity is a free parameter in our computational model that can be leveraged to measure data sources and their correlations in a certain scale. For example, crowd gathering activities have a larger granularity, covering data sources on a larger scale; while traffic accidents have a smaller granularity, requiring more fine-grained information.

We can depict an event granularity, $\boldsymbol{e}$, in both temporal and spacial space, denoted as e_{τ} and e_{σ} respectively. The temporal granularity, e_{τ}, refers to temporal scales, e.g., "1 min" and "1 h" are two temporal resolutions for representing an event. The spacial granularity e_{σ} refers to spatial scales, e.g., "1 m" and "1 km". Imagine a simple case that a user requires an analysis on "tracking a bus with a 1 min temporal resolution". In this setting, "bus" denotes the spatial resolution and "1 min" depicts the temporal resolution.

Furthermore, the spacial granularity has abundant connotations for different sources in our computational model, denoted as $e_{\sigma} = (e_{\sigma}^{p}, e_{\sigma}^{c}, e_{\sigma}^{s})$. Each connotation is determined by features of the data sources. To be more specific,

- The spatial resolution e_{σ}^{p} for physical data p indicates the continuous variations in distance space, e.g., "1 m", "100 m" and "1 km" are three exemplary spatial resolutions.
- The spatial resolution e_{σ}^{c} for information data corresponds to the scale of information, which has different meanings for various information source devices. For example, e_{σ}^{c} for satellite images is the display resolution of the image, it relates to distance space for astronomy simulation data.
- The spatial resolution e_{σ}^{s} for social data corresponds to the scalability of the social factors. For car trajectories, e_{σ}^{s} can be represented by spatial distance. Crowd social networks can be described with the concept of crowd scalability, e.g., "1000 people", "10 people" and an individual.

Dynamic update: Our computational model is able to support dynamic updates of data sources. As depicted in , with the feedback of Δ^i for the ith iteration, the original quasi-holography data $\hat{H}^i$ for an event will be updated to $\hat{H}^{i+1}$. The process is easily extended to support new iterations with dynamically updated data.

4. Case study

In this section, we demonstrate how to leverage our quasi-holography computational model for urban event analysis with two case studies: one regarding congestion exploration and the other on conceptual analysis for public security control.

4.1. Case I: Congestion exploration

The fundamental idea of our quasi-holography computational model – *sampling appropriate data for a specific event and making decisions with dynamically updated information* – can be applied to increase the effectiveness of urban event analysis. In this section, we apply our computational model to analyze an urban traffic congestion case (Chen et al., 2017).

Fig. 3 illustrates the interactive tool for urban traffic congestion. As depicted, city managers often wish to locate congestion and find the cause of congestion and traffic jams. In the very beginning, the accessible data are taxi trajectories (social space data), denoted as $\hat{H}^0$. Our quasi-holography computational model takes $\hat{H}^0$ and the event as input. $\hat{H}^0$ appears sufficient in locating two congestion streets (see Fig. 3(a)), but not indicating its reasons. Our computational model suggests more data sources to help explore the reasons: city structures (physical space data) and POI data (cyber space data), denoted as Δ^0. With the additional data sources, the city managers find that one congested street is located on the region with many automotive service shops where taxis are going for maintenance (see Fig. 3(b)), and the other congested street is near a commercial center (see Fig. 3(c)). The city managers provide interactions to explore the duration of the congestion on the second street, and the corresponding information is shown as a partial view of the quasi-holography data Δ^1 (see Fig. 3(d)).

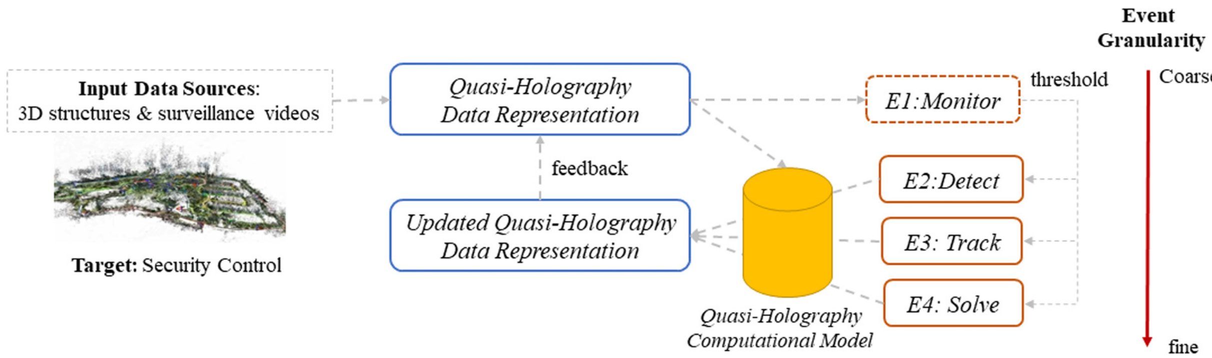

Fig. 4. Illustration of our case study II.

4.2. Case II: Public security control

Our computational model can be leveraged to provide appropriate data sources for analyzing complex and dynamic urban events, such as security control, intelligent office management and traffic monitoring. We demonstrate how to utilize the quasi-holography computational model through a complete study of a public security control case.

The goals of typical security control in a complex public space encompass: (1) monitoring the security dynamic of the region, (2) detecting possible insecurity trends, (3) tracking crowd congestion incidents, and (4) providing solutions for a catastrophe if necessary. These goals are with different event granularities, and highly related to crowd number and the physical space. The crowd size (social space data), the granularity ranges from the "group" level to the "individual" level; and for physical space, it ranges from the whole square to an individual.

E1: Monitoring the security dynamics of the region. Suppose at the very beginning, only 3D constructions on the square (physical space data) and surveillance videos (cyber space data) are available, which can be considered as a quasi-holography representation $\hat{H}^0$. With data sources in $\hat{H}^0$, we can infer the crowd number and density (semantics layer of $\hat{H}^0$), and consequently evaluate if the crowd density is above a dangerous threshold δ or if the crowd number is increasing too much (knowledge layer of $\hat{H}^0$) semantics information such as crowd density.

E2: Detecting possible insecurity trends. Our quasi-holography computational model will not update the original representation $\hat{H}^0$ until the crowd density is close to a predefined dangerous threshold $|\delta - \epsilon|$. If this happens, our computational model will give alert to the managers and suggest more data sources to avoid the increasing number of visitors. Data sources such as GPS signals from telecommunication companies (cyber space data), passenger data from the Metro office (social space data) and taxi trajectories (social space data) are helpful. With GPS signals, we can estimate the number of visitors on their way. With subway passenger data and taxi trajectories, we can analyze the visitors and suggest them to cancel their schedule or avoid the region with coercive measures if possible.

E3: Tracking the crowd congestion incident. When the crowd density is at a dangerous threshold, our quasi-holography model will update the original quasi-holography data $\hat{H}^0$ to disperse the crowd. Data sources such as online messages from communication companies (cyber space data), trajectories of security guards (social space data), and positions of mobile guard bars (physical space data) can be leveraged to achieve this goal. Online messages help to locate individuals and their status (whether they are within the crowded region or not). Using trajectories of security guards, we can coordinate them to help disperse people. With positions of mobile guard bars, we can move them to build any temporary dispersing path.

E4: Providing solutions for a catastrophe. E3 will evolve to a catastrophe if no solution is effectively executed, e.g., injuries or death caused by the stampede accident. Suppose the quasi-holography data representation before the catastrophe is $\hat{H}^i$, our computational model will reorganize and update $\hat{H}^i$ to $\hat{H}^{i+1}$, providing an appropriate solution to the catastrophe. To achieve the goal, our computational model would suggest additional data sources at the temporal and spatial scale with the finest granularity. Data sources will be requested and updated, such as UAV drones (physical space data), individual ID information (cyber space data), the number of security guards in nearby areas (social space data), and traffic conditions in the surrounding area (social space data). UAV drones are introduced to track and capture the environments and visitors trapped in the catastrophe. The individual ID information helps to analyze an individual's health and former medical history for effective medical treatment. Security guards and traffic conditions in nearby areas will be invoked to help disperse the crowd safely.

The data sources mentioned in E2–E4 are potential feedbacks from our quasi-holography computational model, which updates the original data representation to a new one for analyzing an event. Fig. 4 shows the iterative process. This case study demonstrates a typical analysis process of our quasi-holography computational model, which can be easily extended and applied to more complex and dynamic events.

5. Potential problems

Our quasi-holography model demonstrates significant compatibility for data analysis adapting to events of different natures. However, there are still quite a few potential issues to address with the proposed model as discussed below:

Multi-events joint optimal computation: One goal of the proposed model is to provide interactive computational analysis and optimal guidance for processing a specific event. When multiple events or conditions occur simultaneously, they bring multiple constraints, thus the output results need to be optimized based on the co-occurrences. Consider an "urban traffic congestion" occurring in a "restricted area with potential security problems" on a rainy day, obviously, an optimal solution for this case would not be optimal for another. How to solve such multi-objective optimization problem becomes important.

Self-evolution data representation: Our *holography data representation* is a spatial and temporal framework to depict data, information and knowledge in the entire world. For a dynamic event that is constantly unfolding and developing, the incoming data are frequently updated, how to define a self-evolution data representation and how we best explore temporal coherence, are essential issues to address.

6. Concluding remarks

Multi-source and heterogeneous data captured from different sensors in urban space is highly decentralized and fragmented, which pose great challenges to urban computing and applications. In this paper, we propose a concept - *holography data representation* - to unify data sources and their correlations based on temporal and spatial information. Based on the *holography data representation*, a novel event-driven quasi-holography computational model is defined, which can measure the sufficiency of data sources and choose appropriate data to analyze a given event. Two case studies are presented to further explain the quasi-holography computational model. Finally, We discuss two interesting problems to solve when extending and implementing our quasi-computational model. Though our model is proposed as a conceptual framework, it builds the bridge for analysis of efficient data and on-the-fly event. We shall leave it to future efforts to maximize the usage of the quasi-holography computational model in large-scale urban computing.

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Declaration of competing interest

There are no conflicts of interest.

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