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Edge Computing in Context Awareness: A Comprehensive Study †

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Abstract: Mobile edge computing (MEC), which is now gaining a lot of momentum, allows users to use its services with low latency, location awareness, and mobility assistance to offset the drawbacks of cloud computing. The quality of the experience, reduced latency, and boosted performance are the ultimate context-aware goals. There have been many context-aware efforts in the past. In this study, we reviewed many elements of the proposed context-aware approach for edge cloud computing, including their benefits and drawbacks. Additionally, we looked at such context-aware techniques to determine which were practical given the situation. We anticipate that the survey will be carefully considered in the creation of new context-aware methods. Future directions and problems have also been looked at.

Keywords: cloud computing; edge computing; context awareness; classification of context awareness

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1. Introduction

Edge computing became popular after the introduction of 5G networks and the Internet of Things. The mobility of applications and edge computing depends on the geographical distribution of resources. A node for edge computing only benefits those nearby. Since cloud computing allows application mobility by setting the location of the server and sending data to the server over the network, the mobile management of the application in edge computing is an entirely new approach. Context awareness in mobile computing is currently an effective approach for developing adaptive universal computing applications. One of the basic elements of ubiquitous computing is context awareness. Any information that can be utilized to describe the condition of an entity is considered a context. The user-related context (such as activity, mobility, and social interaction), the application-related context (such as application type, latency sensitivity, and application architecture), the physical or environmental context (location, time), the network-related context (such as bandwidth, network condition, communication, and traffic), and the device-related context (such as available resources, dataflow, and data size, remaining battery) are common context types. If a system can adjust its behavior to a specific scenario and provide appropriate data and/or services, it is said to be context-aware.

1.1. Cloud Computing

Until the introduction of edge computing, conventional cloud computing centralized storage and computational problems by sending all data across the network to the cloud computing center [1]. Today's cloud computing has evolved. It offers a very strong basis for network services with distributed computing, balance of load, computing in parallel, network storage, and other technologies. But as the World Wide Web of Things permeates more aspects of everyday life, more devices are linked to it, and as a result, more data are being generated. The network bandwidth required for dependent-on-time applications and immediate efficacy has not been met by cloud computing [2].

1.2. Fog Computing

Fog computing seeks to minimize network traffic and latency between client devices and cloud servers. A fog node in fog computing systems may be overloaded due to an increase in end device requests. To address the needs of fog computing in this situation, an effective offloading mechanism among fog nodes is required. The size of the hardware components associated with these computing paradigms is largely responsible for the distinctions between cloud and fog computing. The high availability of data is provided through cloud computing. Computing resources have a proportionally high power consumption, while fog computing offers a reasonable availability of computing resources with a lower power usage [3].

1.3. Edge Computing

Edge computing is typical of conventional cloud computing. It may be a neglected computing perspective that handles processing at the array's boundary. Its main objective is to make the calculation more connected to an accurate data source [4]. Edge computing aims to be the Internet of Things (IoT) solution of the future that solves a variety of issues, especially those associated with dependence on time and computation-based applications. Data processing with the network edge has several benefits, including lowering communication and collaboration burden; dismantling big designers [5]; providing enhanced efficiency, safety, and confidentiality; enabling tiny and big developers to participate in fostering future innovations; lowering the energy consumption of mobile nodes; and removing congestion from the main network (Figure 1).

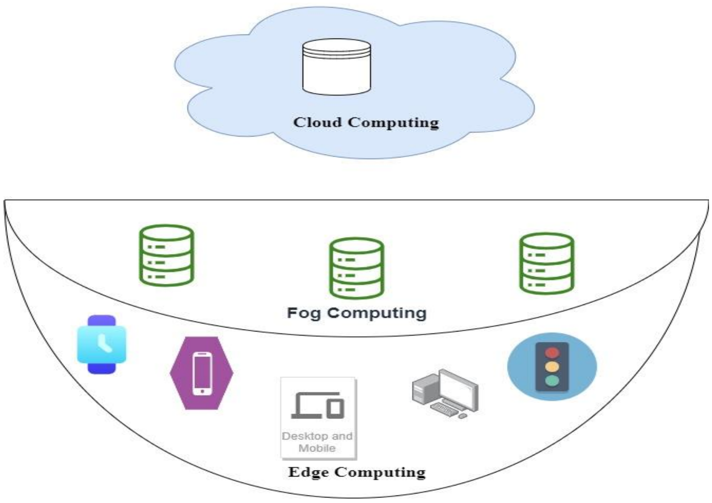

Figure 1. The cloud, fog computing, and edge computing scenario.

1.4. Paper Contribution and Organization

A complete, comprehensive review of the research on context-aware mobility in edge computing is presented in this article. It gives a thorough investigation of the context awareness that various edge computing entities currently offer. The goal of this case study is to help authors decide what further studies to pursue and obtain knowledge about how to produce context awareness by using and improving QoS (Quality of Service) needs. The following are this paper's key contributions: A comprehensive review of context awareness is conducted, and its categorization is established. Mobility is compared based on essential components such as context-aware characteristics and efficiency measures, each with advantages as well as limitations.

The remaining section of the paper is structured as follows:

An overview of recent surveys on context awareness in edge computing is given in Section 2. Section 3 discusses context awareness, contextual information, context representation, context modeling, and the classification of context awareness. Section 4 discusses challenges and future directions. Section 5 concludes this paper.

2. Related Work

For context-awareness based on cloud, fog, and edge computing, many surveys have been proposed. In the next part, we evaluate comparable survey publications and discuss their advantages and limitations. Table 1 summarizes these subsections and compares them with our survey.

Table 1. Summary of edge computing in context: awareness of advantages and limitations used in this paper.

Author (Year)	Mechanism	Algorithms Used	Metric	Advantages	Limitations
Truong, H. L.; et al. (2023) [6]	DEML-RCCE (Distributed edge machine learning and resource-constrained communities and environments) design	Machine learning	Analyzed many businesses, infrastructures, costs, and operation-related scenarios	Edge computing and machine learning also remove barriers based on a lack of effective cloud data centers.	Edge machine learning solution development and deployment for vital IoT-based business applications.
Liu Z. et al. (2022) [7]	Two context-aware QoS schemes	ABC (artificial bee colony algorithm) algorithms	Prediction accuracy	Location awareness, mobility support, and reduced latency are among the features that MEC makes available for use.	User mobility is not predicted by QoS for MEC services.
Chen Z, et al. (2022) [8]	DMCPA-GS -online with Gibbs sampling	Lyapunov optimization.	Efficiency, privacy, reliability, and security	To reduce both energy consumption and user perception of latency.	Under predictable delays and limited edge resources.
Aranda J. A., et al. (2022) [9]	Smart grid	Machine learning	Predict energy consumption and reduce delay	In operating as edge computing nodes, network stability is taken into account to deliver data efficiently.	The adaption occurs when the SG (smart grid) network has a high latency.
Yang, Y, et al. (2022) [10]	Web VR (virtual reality) services, web VR feature map	Clustering, LADMM (low bound-based alternative direction method of multiplier) algorithm	Maintain resource utilization and delay performance in check	To reduce system energy usage by optimizing the offloading mode, task allocation, and processing power resources.	Implementing high-speed transmission technologies like millimeter waves and the terminal's processing power.
Salami B, et al. (2022) [11]	Task scheduling (software-defined network)	Deep reinforcement learning	Latency, energy efficiency, and network scalability	Energy awareness provides more effective savings on energy of up to 87%.	Battery power and the offloading strategy may complete more job assignments with a 50% reduction in time delay.

Table 1. *Cont.*

Author (Year)	Mechanism	Algorithms Used	Metric	Advantages	Limitations
Fu M, et al. (2022) [12]	EC-SIARA SYSTEM	Deep learning	Time(s) and accuracy	AR (augmented reality) assembly processes increase assembly effectiveness and significantly decrease the occurrence of assembly problems.	Assembly performance, as well as the rate at which new assembly methods are learned.
H. Zhang et al. (2022) [13]	Distributed resource allocation method	Federated learning, the decision algorithm	Average delay, cost	To decrease the extra cost that federated learning offers.	Fewer devices to take part in federated learning.
Zhou, P, et al. (2021) [14]	Trustworthy collaboration, trust evaluation factor	context-aware distributed online learning algorithm	User evaluations, content hit rates, and running time	To increase mobile edge computing service performance.	The ability to cache the content is frequently viewed as favorable.
G. Tefera et al. (2021) [15]	Distributed computation offloading, RAN (radio access network)	DARMEC (decentralized adaptive resource multi-access edge computing) algorithm	Scalable, ultra-reliable, and low latency	Resources for storage, communication, and computing.	A caching system that can adapt to manage the MEC networks' structural complexity.
Shahidinejad et al. (2021) [16]	Context-aware offloading	FL-based offloading algorithm	Energy consumption, total execution cost	Context-aware data and distributed structures may increase network performance.	Communication security problems like distributed DoS (denial of service) and jammer attacks are a concern for FL.

M Ma, et al. [17] propose enabling real-time context awareness and decision-making in IoT edge systems with a high-efficiency joint event inference model to allow multi-pattern optimization. We construct several types of redundancy relations across event inference models and provide an explanation mechanism called an event-containing graph. Merge, fail, and output are three operations on single-pattern event inference models.

Chatterjee et al. [18] provide the most efficient techniques for in-sensor analytics that allow for the measurement of energy usage in a large area. Through event-driven communication of temporally compressed data without losing more than 1% of the information, spatial data compression with collaborative intelligence, and context-aware cluster head switching during CI for a longer network lifetime, WSNs (wireless sensor networks) reduce the degree of duplication in the transmitted data.

Zhao, P, et al.'s [19] network with context-UCB, a model-free online ML method, has been presented as a resource allocation technique. It may provide an image of AI by dynamically adjusting the TDD configuration for each period based on the localized environment and MAB.

Liao, H, et al. [20] proposed a manner of training the selection that considers service security, energy use, and backlog awareness and can increase throughput by between 30% and 36% compared to random selection and the UCB.

Chen, X, et al. [21] presented C2-EXP3, a context-aware EXP3-based channel selection method for CM2M communications with the coexistence of licensed and unlicensed spectrum. Comparing C2-EXP3 to EXP3, random selection, C2-UCB, and UCB, C2-EXP3 may increase utility by 5.77%, 15.06%, 48.29%, and 59.91% while stabilizing the data queue and meeting the constraints of energy usage and service stability.

3. Context Awareness

"Any information that can be utilized to characterize the situation of an entity" is referred to as context. A person, place, or thing that is considered important to the relationship between a user and an application is known as an entity [22].

3.1. Contextual Information

The term "context" can also refer to a description of a particular entity scenario, such as a user's profile, environment, social interactions, or activity. We may, for instance, create the context based on location information and the entity based on the user by enhancing the individualization and usability of sensor network services; context becomes a much richer and more powerful term in this sense, especially for mobile users.

3.2. Context Representation

In context-aware applications, a sensor is described as both a physical object and a potential data source. For the representation of context, in terms of the specification and projection of an occurrence onto a thing in the digital world from the real world, the collected contextual information may vary significantly.

3.3. Context Modelling

An efficient context modeling strategy tries to make programs more adaptable and maintainable for future development while lowering their complexity for robustness and usability. To be able to achieve that, a variety of context sources from any level of abstraction must exhibit variability (i.e., defects of a dynamic nature), similarity (i.e., the presence of identical context from different sources), and mobility (i.e., delayed, timeless data collection).

3.4. Classification of Context Awareness

The low-level contexts that correspond to the different levels of complexity are then used to identify the high-level context, the context of the device, such as its net connectivity, the resources and cost of communications, etc. User context includes the user's profile, location, neighbors, and social context, among other things. The environment includes things like humidity, volume, brightness, and traffic conditions. Historical context comprises, among other things, the current day, week, period, time of year, (Figure 2), etc.

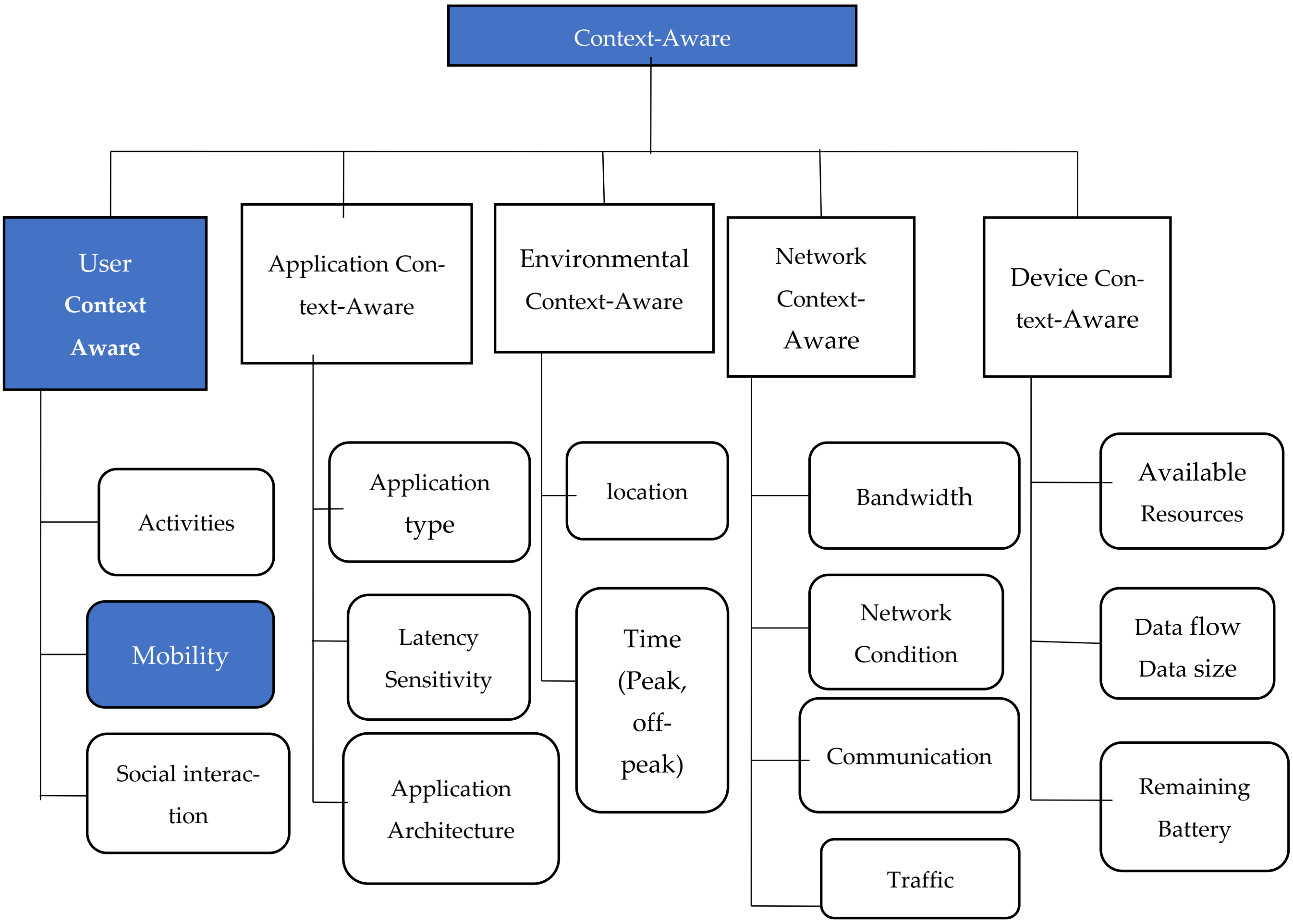

Figure 2. Classification of context awareness in edge computing [22].

4. Challenges and Future Direction

The prospective priorities for this study are derived from the comprehensive evaluation of the research, including designing a user-context-aware mobile experience based on awareness of context at various levels and contextual information for mobile devices and users to improve communication and computational support, as well as optimizing resource use and meeting deadlines for service delivery, taking advantage of mobility and user-customized settings, and developing an approach that is effective for obtaining and utilizing cross-domain connections. The notion of exchanging context and minimizing the delay for context sharing across edge nodes and creating efficient mobility management while taking device power and mobility reliance into account and enhancing application placement rules by combining user- and device-level contexts was also analyzed. Utilizing context information like budget, cost, and time to react, mobility management was evaluated. Using interoperability to fulfill QoS criteria requires context awareness.

5. Conclusions

The context awareness of the edge computing paradigm and a complete literature analysis are presented in this study. The outcomes of this survey have been investigated in several ways. Use application, device, environmental, network, and user contexts are the five categories it uses to categorize the context of edge computing. Furthermore, the use of context-aware parameters and performance indicators, along with an evaluation of various strategies and a thorough analysis of all parameters, were studied. Additionally, the benefits and drawbacks of each context-specific method were examined. The edge cloud is still in its early stages, so more work is still needed. We predict that the survey we have just provided will serve as an entry point into the edge cloud world and be advantageous for both the research and business communities.

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