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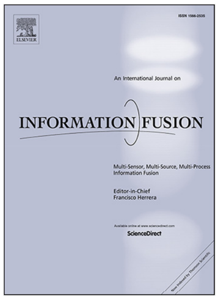

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Information Fusion for Edge Intelligence: A Survey

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Abstract

Edge intelligence capability is expected to enable the development of a new paradigm integrated with edge computing and artificial intelligence. However, due to the multisource nature, heterogeneity, and a large scale of the sensory data, it is necessary to improve the data processing and decision-making capacity for the edges. Hence, this paper asserts that information fusion is an important technique to power the capacity of edge intelligence in terms of collection, communication, computing, caching, control and collaboration. Specifically, it provides a comprehensive investigation of four representative scenarios assisted by information fusion at the edge, i.e., multisource information fusion, real-time information fusion, event-driven information fusion, and context-aware information fusion. Moreover, it discusses the future directions and open issues in this field.
Keywords: Information fusion; multisource; real-time; event-driven; context-aware

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1. Introduction

In recent years, due to the rapid increase in the number of network terminal devices and the quantity of data they generate, artificial intelligence based solely on the cloud has had some shortcomings. Due to these shortcomings, edge intelligence came into existence. It deploys artificial intelligence in the edge network and emphasizes being close to the source of the data to reduce the delay in the delivery of intelligent cloud computing services. In addition, it realizes the true sense of wireless situation intelligent perception, intelligent rapid decision-making and real-time response [1].

Edge intelligence aims to combine edge computing with artificial intelligence and other applications. Then, it syncs the data processing capability based on cloud computing to the edge nodes to provide advanced data analysis, scene perception, real-time decision-making and other service functions in the edge network. According to the development trend of edge intelligence technology, edge intelligence consists of the following 6 functions:

1. Collection
   Sensors are the front-end components of edge intelligent application systems. Combined with sensor technology, edge devices can obtain data efficiently. Especially in smart buildings and smart home systems, many edge devices are integrated with sensors to collect data in real time.For example, smart passive sensors (SPSs) [2] are wireless batteryless sensors that can monitor various parameters, such as temperature, pressure, humidity or distance, in the edge network. iDAR (intelligent detection and ranging) [3] is a micro-optical-electromechanical-system (MOEMS) lidar integrated with a low-light camera, and it also has embedded artificial intelligence algorithms for real-time sensing of the surrounding dynamic environment. The widespread use of these edge intelligent devices provides a rich data source for edge intelligence. However, edge sensor devices may be constrained by energy, bandwidth or raw computing power. The bandwidth limits the maximum rate at which data can be collected from sensors

and are transmitted downstream. This may bring challenges to programming, and may sacrifice some benefits. Ideally, sensors should only send absolutely necessary information, and critical data can immediately make critical decisions. In addition, edge sensors that are small in size and unobtrusive, can be easily deployed in space constrained environments. This kind of edge sensors can be placed anywhere that is possible to perceive valuable information, not just where existing communications and power infrastructure is located.

2. Communication
The large quantity of data collected in the edge network poses a great challenge to the data transmission ability. As a result, many edge-oriented communication technologies have emerged. The device-to-device (D2D) approach is used to provide services such as real-time data transmission and sharing, which plays a key role in the edge intelligence framework. D2D communication technology, unlike the traditional network-centric data transmission mode, opens up a device-centric communication direction, which can effectively increase the communication capacity of the edge network [4] and provides the necessary data transmission and information sharing capability for edge intelligence. Communication theory and techniques can substantially bridge the capacity of the cloud and the requirement of devices by the network edges, thus accelerating content delivery and improving the quality of edge system services. To bring more intelligence to edge systems, deep Reinforcement Learning techniques and Federated learning frameworks have been integrated for optimizing edge computing, caching and communication [5].

3. Computing
With the improvement of edge device performance, the edge network has sufficient computing resources. With the help of edge computing technology, data can be processed in the edge network in a timely and effective manner [6]. Edge computing has played a considerable role in many fields [7] and is widely used in medical care [8], mobile data analysis, the inter-

net of Vehicles [9, 10], wireless sensor networks and in other scenarios [11]. In particular, the use of edge computing can considerably reduce the waiting time of applications and services, thereby improving user experience. Therefore, edge computing is regarded as an important component of edge intelligence, which aims to reduce response time, save bandwidth, reduce network traffic and energy consumption [12], and ensure data security and privacy [7].

4. Caching
   In recent years, many studies have focused on the deployment of caches in edge networks [13] to relieve core network congestion and reduce end-to-end waiting time to improve network performance. Unlike traditional data storage, edge caching only temporarily stores real-time information on edge devices to improve the information distribution capabilities of edge devices. In particular, a study [14] advocated the use of predictive information requirements and active caching on the base station and user equipment, thereby greatly reducing the peak traffic demand. Therefore, edge caching provides powerful information-sharing capabilities for edge intelligence and improves information utilization efficiency.
5. Control
   With the popularization of the industrial internet, autonomous driving, smart homes, smart transportation, smart cities and other technologies, the requirements for real-time control and feedback capabilities of devices in the edge network environment are increasing. For example, in terms of public safety, the authors in [15] proposed a shared car unsafe event detection system based on edge computing, called the SafeShareRide system. Specifically, the mobile phones of drivers and passengers are used as the edge end. Through voice recognition and driving behavior detection, video recording and processing mechanisms (mobile terminal compression, cloud analysis) are triggered after abnormal behaviors are detected. Also, on-board video records are analyzed to monitor the safety situation of passengers. In edge networks, edge intelligence can autonomously control edge

devices according to specific tasks and provide users with corresponding services, effectively avoiding the high-latency defects of traditional cloud-based control systems [16]. For example, the smart cruise control system is a set of environmental perceptions for planning and decision-making, multi-level driving assistance and other functions in one of the comprehensive systems. The information collected by sensors, such as cameras and radars, is sent to the control computer to extract features. Additionally, driving data information is obtained through model calculation to master comprehensive and complete driving habits, helping semiautonomous driving vehicles make decisions and control. In addition, for some mission-critical functions, edge computing cannot tolerate any delay. This requires high-precision real-time analysis and control to perform calibration to minimize defects. According to different applications and data sizes, solutions suitable for different control situations are required. Real-time data acquisition and millisecond-level control were committed to achieve real-time control of applications.

6. Collaboration
With the support of edge intelligence technology, edge devices can make full use of the advantages of geographic proximity and segmentation (for example, changes in application scenarios and user requirements) and cooperate to accomplish a series of tasks, improving users' daily experiences and quality of life [17]. The authors in [18] proposed social sensing-based edge computing (SSEC) using edge devices close to users (mobile phones, tablets, smart wearables and the Internet of Things) as pervasive sensors. A federation of computing nodes was formed to perform sensing, storage, networking, and computing tasks near the data source. The authors in [19] combined artificial intelligence (AI) with edge computing and proposed the concept of collaborative intelligence to reduce the computing burden of edge devices in applications running on deep neural networks (DNNs). Collaborative Intelligence (CI) is an AI deployment strategy that leverages both edge-based and cloud-based resources to make DNN

computing faster and more efficient [20].

In summary, edge intelligence can meet the key needs of industry digitization in terms of agile connectivity, real-time services, data optimization, application intelligence, and security and privacy protection. Meanwhile, data convergence can effectively facilitate large searches in cyberspace and contribute to the construction of knowledge graphs in the edge intelligence domain, creating considerable social and economic benefits [21].

In the edge intelligence framework, intelligence is pushed from the cloud core to the edge devices to better support timely and reliable data analysis and service response. However, there is no central control point in the edge intelligence framework, and middleware from different organizations have their own solutions for sensor connectivity, collection, modeling, and contextual reasoning [22]. Therefore, it is important to fuse information between solutions from different types of middleware. Information fusion is a recognized area of technological research and advancement in recent decades [23], Multisensor information fusion techniques [24, 25] in edge intelligence devices are rapidly evolving [26].

With limited network resources, information fusion technology further optimizes the cost and performance of edge intelligence, and edge intelligence combined with information fusion technology provides the corresponding function-s for different situations. Edge intelligence generates and collects information through sensors, terminal devices, etc., and provides more powerful performance and storage space for edge nodes through information fusion to extract useful information, analyze and process it to provide corresponding functions for different situations [27]. Since the objects served by edge intelligence as well as scenarios are more diverse, making a set of edge intelligence platforms adapt to diverse third-party applications is a current problem. Thus data fusion is the key to building edge intelligence.

The main contributions of this survey include:

1. This paper introduces the principle and application of typical information

fusion methods.

2. The survey classifies edge information fusion methods in four representative scenarios.
3. This paper also summarizes the problems and challenges in the information fusion of edge intelligence.

This paper conducts a comprehensive investigation of four representative scenarios assisted by edge information fusion. In the second section, we outline and discuss the basic principles, related applications and current challenges of the five types of information fusion methods: multisource information fusion, real-time information fusion, event-driven information fusion, context-aware information fusion and collaborative information fusion. In the third section, we introduce in detail the classification of edge information fusion methods in four types of scenarios: multisource information fusion, real-time information fusion, event-driven information fusion and context-aware information fusion. In the fourth section, we discuss future directions and unresolved issues in this field. Finally, we conclude this article.

2. Main information fusion methods

In this section, we will review and discuss the underlying rationale, related applications, and current challenges of the main information fusion methods.

2.1. Multisource Information Fusion

Multisource information fusion refers to the technology of combining and merging information or data from multiple sources to form a unified result. The process uses technical tools and data methods to comprehensively process information from different sources. Through the optimized combination of information, we can obtain high-quality effective information. In summary, information fusion is a process of providing integrated information system users with a unified view of multiple data sources [28]. The purpose of multisource information fusion is divided into two aspects. One aspect is for the redundancy of multisource information and to eliminate noise and outliers in the input information. The second aspect is for the complementarity of multisource information, acquisition and practical application of related valuable information, and to maximize the complete information description of the observed object [28].

A single data source has limitations in its application. For example, in geological exploration, complex underground geological structures cannot be fully described by a single dataset. The traditional stratigraphic correlation process produces considerable uncertainty [29], and multisource data fusion can obtain more accurate, complete and reliable estimates and judgments than a single data source. It can help computers better understand human intelligence, human language and human thinking, effectively promote network search and the construction of domain knowledge graphs, and create considerable social and economic benefits [30].

Therefore, multisource information fusion technology has been continuously developed and merges information from multiple directions to obtain enhanced decision-making information. In recent years, it has been applied in the fields of image fusion, industrial intelligent robots and intelligent transportation systems [31], as well as environmental monitoring, smart home appliances, ecological modeling, and global perception [32].

A strategic early warning system is a classical application of multisource information fusion technology in the military field. Other applications of multisource information include autonomous positioning and navigation systems of multirobots and intelligent transportation systems [31].

The main methods of multisource information fusion are as follows:

1. Estimation theory

   Estimation theory uses statistical methods to estimate the parameters or states of the signal mixed with noise received at the receiving end. These include Kalman filters for linear random systems, extended Kalman filters for nonlinear random systems (extended Kalman filters or EKFs) [33], and strong tracking filters (STFs) [34]. With the continuous improvement in people's understanding of information fusion, an increasing number of scholars are committed to the unscented Kalman filter (unscented Kalman filter or UKF) with a second-order approximation accuracy [35] and discrete differential filter (DDF) [36]. The scholar have achieved many valuable research results.

2. Uncertainty reasoning method
   In the multisource information fusion system, the information provided by various measurement sources is incomplete, inaccurate and fuzzy. The detection information contains much uncertainty, and thus, the fusion center, where the information from multiple sources is combined to reach a better inference, can only rely on the determination of information processing and reasoning to achieve goal recognition and attribute judgment purposes. This method is the basis of goal recognition and attribute information fusion, including the subjective Bayesian method [37], DS evidence reasoning method [38], DSm-T method [39], fuzzy mathematical theory method [40], and the possibility reasoning method [41].
3. Theory of intelligent computing and pattern recognition
   Intelligent computing and pattern recognition are the processes of distinguishing things according to certain observed values [31]. At present, theories applied to information fusion include rough set theory [42], random set theory [43], gray system theory [44], information entropy theory [45], neural networks [46], genetic algorithms [47], and Bayesian networks [48].

At present, multisource information fusion faces the following challenges.

1. One challenge is the uncertainty of information. The uncertainty of information refers to the observer's lack of judgment and absolute certainty about objective things [49]. For example, using the depth of the convolutions of the neural network (DCNN) or deep CNN ImageNet question classification result, object recognition performs better than most traditional methods [50]. However, when applied to intelligent refrigerators,

because of the color, shape, and texture of fruit to the same extent, such as oranges, it was difficult to effectively identify foods [51].

2. Another challenge is information source conflict. To make the best use of data, a uniform form of data needs to be obtained from multiple sources, and these different data sources may conflict. For the multisource fusion of knowledge, knowledge maps (KGs) can be built due to the knowledge sources, multisource heterogeneous knowledge between repetition, semantic variety, quality and other issues. We need to conduct conflict detection, entity disambiguation, entity alignment and other operations [30].
3. A third challenge is the loss of information. When there are a large number of sensors, the processing of massive monitoring data not only consumes a large number of computing resources but also blocks the entire information network and even leads to loss of information, resulting in low final accuracy [52].
4. In addition, dynamic multisource data processing is also a challenge. The data collected in practical applications are multisource and dynamic. Interval data are usually used to describe dynamic phenomena, such as temperature changes, stock price fluctuations, and blood pressure. Additionally, interval data can be obtained from many different locations or sources. Considering that the data from multiple sources vary over time, effectively integrating this data is a challenge [53].
5. Finally, data relevance is the last challenge. Heterogeneity of the data structure is manifested in structured data, semistructured data and unstructured data. Traditional multisource data fusion is mainly aimed at the fusion of structured data. However, with the development of sensor technology, the data that need to be fused include more unstructured data. For example, text data are usually represented by discrete word vector features, while images are represented by image pixel features. Data with different structures have different characteristic representations. Therefore, the heterogeneity of data becomes a gap between the association, crossover and integration of heterogeneous data from multiple sources [51].

2.2. Real-Time Information Fusion

Edge computing is widely used in the analysis of real-time and short-period data. In practical applications, two types of data are usually generated [54]: real time and non-real time. Real time data is usually generated due to the occurrence of specific events. Non-real time traffic is generated by routine inspection tasks, with no time limit. In this case, it is necessary to combine data from different time domains in different forms.

Real-time fusion aims to detect events quickly [54], obtaining new information in time from a large quantity of data continuously generated from different sources [55]. This efficient discovery mode enables data sources to be processed effectively and in a timely manner. Fig. 1 is based on the fusion system to collect multisource information, and the use of a parallel processing mechanism can substantially improve the speed of information transmission and processing to increase the real-time nature of the system. To effectively process incremental data in the real world and continuously obtain information from new data, many real-time fusion methods have been proposed.

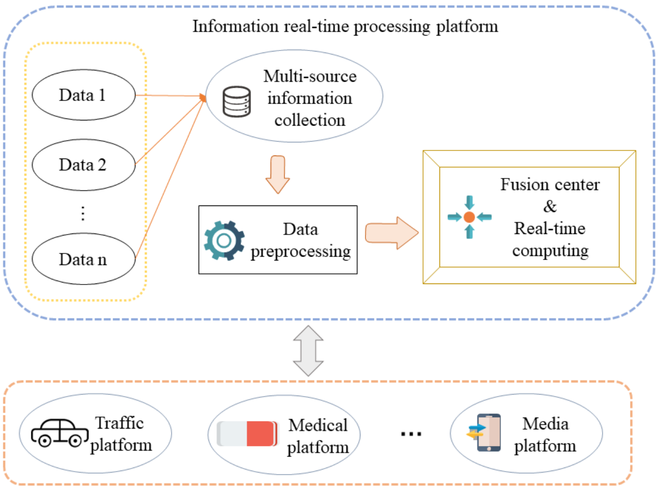

Figure 1: Conceptual model of real-time information fusion

In the video environment, the video image scenes from multiple cameras are fused for real-time object recognition, target tracking and self-localization [56, 57, 58, 59]. For vehicle traffic, multiple sensor traffic information fusion, real-time traffic data monitoring and accident detection, and improvement of real-time transportation services [60, 61, 62, 63] can be achieved. In the medical background, fusion technology is applied to deep learning of medical image data, real-time data and heterogeneous data, which are efficiently fused. Also, clinical disease data are processed in real time [55]. Under the communication mechanism, the multimedia stream data provided by the edge cloud distributes information fusion, an online traffic scheduling strategy is implemented, and multimedia real-time application is performed [54, 64].

In the video environment, the video image scenes from multiple cameras are fused for real-time object recognition, target tracking and self-localization [56, 57, 58, 59]. For example, the ORB-SALM2 method achieves indoor mobile robot positioning by acquiring image posture and spatial modeling of the scene. For vehicle traffic, multiple sensor traffic information fusion, real-time traffic data monitoring and accident detection, and improvement of real-time transportation services [60, 61, 62, 63] can be achieved. In the medical background, fusion technology is applied to deep learning of medical image data, real-time data and heterogeneous data, which are efficiently fused. Also, clinical disease data are processed in real time [55]. Under the communication mechanism, the multimedia stream data provided by the edge cloud distributes information fusion, online traffic scheduling strategy is implemented, and multimedia real-time application is performed [54, 64]. For example, the CSMA algorithm uses real-time information fusion to deliver sensor data and quickly detect events to monitor specific scenarios.

Currently, real-time information fusion technology mainly has the following key problems:

1. One key problem is the high cost. A large number of sensors continue to generate and transmit data. In the real-time fusion process, it is easy to generate a large amount of redundancy and error information, which

makes the calculation cost and application cost of data fusion high [57, 61, 62].

2. Another key problem is the dynamics. In complex and changeable scenarios, the environment changes over time. For example, user movement and vehicle movement will form a dynamic data stream, and that the data also changes over time [65]. Therefore, reliable data collection and real-time information fusion are essential for task performance.
3. Uncertainty is another key problem with the technology. Due to factors, such as the development environment, operating conditions, measurement equipment, and the technology used to extract and process information, a certain degree of inaccuracy and uncertainty in the measurement may be affected [58, 62], which brings additional challenges to data fusion [66].
4. The final key problem is with data transmission. The nondeterministic delay and traffic loss in the data transmission process make it difficult to complete large-scale real-time information fusion within the specified time, which causes performance loss [64].

For these real-time fusion problems, it is necessary to accurately obtain dynamic data, reduce time costs, fuse uncertain data, eliminate the impact of inaccuracy, and choose effective methods to reduce delay according to computational complexity and execution time [67]. Edge computing is distributed and close to the device, which can support the continuous acquisition of information from new data for information fusion, improve the accuracy of information fusion, better support the real-time processing and execution of local businesses, contribute to cloud data collection, and support the big data analysis of cloud applications.

2.3. Event-Driven Information Fusion

An event refers to the change or migration of the state, and the state is the division of the characteristic state of the object (entity) to be detected in the research environment. When an event changes the state, the change in the state becomes the prerequisite for the next event, thus forming an event-driven process. As shown in Fig. 2, a basic event-driven information fusion system should include three parts [68]: an event-triggered perception layer, an information fusion layer and an event-driven service layer. The event source in the event-triggered sensing layer includes sensing hardware entities and real-time collected entity attribute information. When the event-triggered rules are met and when the entity or entity attributes change, the various underlying data collected by the event-triggered sensing layer are fused in an information layer convergence and fusion, which becomes the main information processing task of the information fusion layer. The event-driven service layer is integrated upward into various information or scheduling systems to help complete functional services such as optimized scheduling, forecasting, and decision-making.

Event-based scheduling is particularly suitable for resource-constrained application scenarios, especially in wireless sensor networks [69]. Common tasks include event-based multisensor fusion, event-triggered fusion estimation [70], and effective target detection information fusion [71]. Event-driven information fusion has also been applied to financial scenarios. In [72], stock-related event information extracted from online news and user sentiments on social media were used to predict stock trends. In industrial production [73], event-driven information fusion was used for monitoring and process planning in dynamic and distributed manufacturing environments. Event-driven information fusion can also be used to deal with emergencies on traffic roads [74].

Event-driven information fusion technology is widely used in many fields, but it still faces many challenges.

1. The effectiveness of event-driven triggering strategies
   In different application scenarios, event-driven information fusion technology enhances its usability by establishing different event-triggering strategies. In the photoelectric sensor network, a multichannel decoupling event-trigger strategy was proposed in [75], which improves the utilization of network communication resources when communication resources are

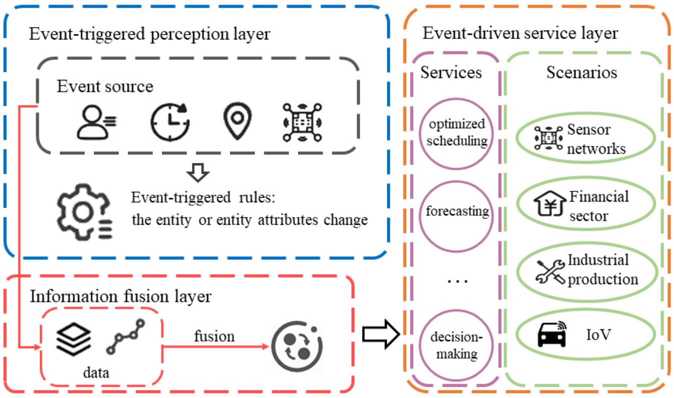

Figure 2: Event-driven information fusion

limited. In a large-scale surveillance sensor network, the authors in [72] trigger event-driven detection by detecting whether there are abnormal electromagnetic signals in the monitored area. Then, they achieve the purpose of moving target detection. Event-driven control strategies will vary according to the event-driven environment.

2. The rapidity of event response

   The uncertainty of the event will increase the energy consumption and data redundancy of the wireless sensor network. When an event is triggered, quickly responding to the event is also an important challenge. In [76], a visual measurement method based on the importance of events was proposed, which can adaptively display real-time video streams to promote rapid responses to events and help security personnel intuitively prevent events. In [73], by introducing an event-driven method using IEC 61499 function blocks, real-time monitoring data of the production workshop were used to adapt to the dynamic changes in the manufacturing environment.

3. Time variability of the event

   It is well known that almost all real-time practical systems have time-varying characteristics [77, 78]. Therefore, the study of transient behavior within a limited time range has greater advantages than a steady-state performance under normal conditions. The time-varying nature of events is a major challenge for event-driven information fusion technology. Measurements from different sensors may be missing, and the probability of missing data may be uncertain [78]. Especially in some cases, the phenomenon of missing measurements may change over time. Thus the corresponding probability of occurrence cannot be accurately obtained.

Event-driven information fusion technology saves limited computing resources and network bandwidth by reducing unnecessary data transmission on the network and can also improve resource utilization efficiency, extending system life. Information fusion is conducive to further mining the value of data, enhancing the role of information analysis, and preventing decision-making errors.

2.4. Context-Aware Information Fusion

With the emergence of a large number of edge intelligent devices, information fusion research has entered a new era [79]. The authors in [80] proposed that context-aware information fusion has high intelligence and flexibility, which can make related devices adaptively provide more satisfactory services. Context is any information that can be used to characterize the situation of an entity [81]. Context-aware information fusion can provide domain-specific solutions that describe the interactions between the observed scenarios and entities. As discussed in [82], context can play a vital role at any level of a modern fusion system from object recognition through physical context exploitation to intention through linguistic communication analysis. Context can understand the relevance between the situation space, the observed data, and the corresponding model, and edge intelligence devices can make decisions or provide services according to the context, enabling them to be safely adapted to the deployed environment [83]. According to the semantics provided by context, the data can be fitted better, and the performance of information fusion can be improved [84]. This method not only reduces the computational burden of the information fusion process but also reduces the response time of the equipment, thus reducing the energy consumption of the infrastructure. As shown in Fig. 3, common scenarios for context-aware information fusion applications include smart homes, health-IoT, environmental monitoring, and intelligent traffic systems (ITSs).

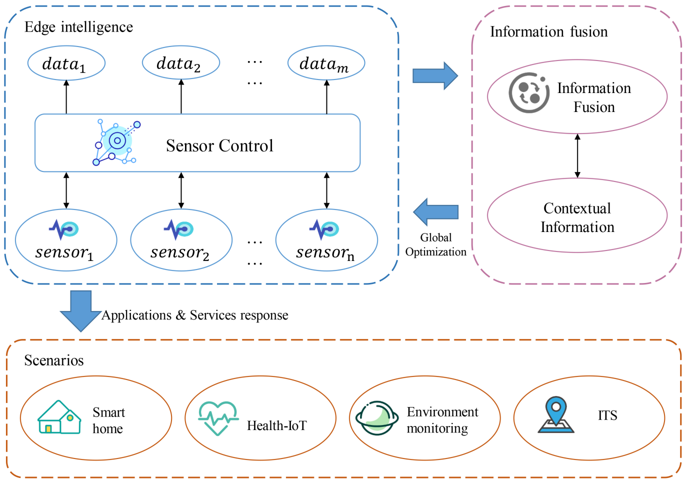

Figure 3: Context-aware information fusion scenarios

The authors in [79] proposed the concept of context awareness at the IoT edge by allowing an object to compute the spatiotemporal influence of the environment observed by nearby IoT devices, on its provided service. The authors in [85] proposed a context-aware, self-optimizing, adaptive system, based on a three-tier architecture, for an ambient intelligence system managing a smart home environment. The authors in [86] exhibited a novel context-aware service framework for IoT based Smart Traffic Management using ontology to regulate smooth traffic flow in smart cities by analyzing a real-time traffic environment. They employed multimedia ontology to derive higher level descriptions of traffic conditions and vehicles from perceptual observations of traffic information which provides important grounds for their proposed IoT framework.

Current challenges to context-aware information fusion include privacy preservation, reliable data collection, and optimal sensor selection:

1. One of the current challenge is privacy protection. In context-aware infor-

mation fusion, data related to smart homes are sensitive to privacy [87]. For example, data on lights can indicate whether a household is at home. While data in the health-IoT domain carry user health information, the information is very personal. Data in the environmental monitoring scenarios are less sensitive to privacy than the first two, but it still carries some personal information about the user, such as position information. Information fusion without regard for privacy protection can substantially affect user acceptance of related applications [79]. Therefore, privacy preservation is seen as a necessary condition for context-aware information fusion.

2. Reliable data collection is another challenge to consider. The results of context-aware information fusion often lead directly to device decisions, such as remote diagnostics in health-IoT or service responses in smart homes. The results of the fusion of unreliable data can be dangerous for users. Reliable data collection is therefore one of the critical requirements of context-aware information fusion. A sensor failure or external attack can destroy data and result in incorrect information fusion results. The authors in [79] suggest that reliable data collection consists mainly of two parts. One part reduces the quantity of the transmitted data, and the other deals with bad data.

3. A third challenge involves sensor selection. The performance and effectiveness of context-aware information fusion depend on the selection of correct contextual information, and the authors in [85] suggest that strictly necessary sensors can be activated only according to the current requirements of the system, rather than using all available data sources. However, in an edge intelligent network, the presence of hundreds of interconnected devices makes it difficult to find sensors that meet the information fusion requirements [88, 89]. If the importance of related sensors can be evaluated and the quality of related sensors can be improved, the most important sensors can be selected for information fusion, which helps to improve the reliability and robustness of information fusion.

Table 1 summarizes the characteristics of the data and sensors in the above four typical context-aware information fusion scenarios.

Table 1: Characteristics of context-aware information fusion main scenarios

Characteristics	Smart home	health-IoT	Environmental monitoring	ITS
Privacy sensitivity	High	High	Medium	Medium
Sensor distribution	Small area	User centric	Wide area	Medium area
Security goals	Confidentiality	Confidentiality	Integrity	Timeliness

2.5. Collaborative Information Fusion

Along with 5G and state-of-the-art smart Internet of Things (IoT) sensors, edge computing provides intelligent, real-time, low-cost solutions for various ”smart spaces”, such as factory malls, health care platforms, and smart homes. To improve both inferencing accuracy and performance metrics (such as latency and energy overheads), some edge intelligent frameworks combine the two or more information fusion techniques to provide high-quality service to users. In this section, we introduce some collaborative information fusion techniques.

The authors in [55] proposed the iFusion framework, which achieved efficient intelligence fusion for deep learning from real-time data and multisource data. For real-time data, they train only newly arrived data to obtain a new discrimination model and fuse the previously trained models to obtain the discrimination result. For multisource data, different types of data are trained separately. Then, they fuse the different discrimination models, making it unnecessary to consider multisource data formats. They use a method based on Dempster-Shafer theory (DST), which was used to fuse the discrimination models. They applied iFusion to the deep learning of medical image data, and the results of the experiments show the effectiveness of the proposed method.

The authors in [90] proposed a wireless body sensor network that was employed for movement and heart data monitoring. This sensor network combined event-driven and context-aware information fusion techniques to detect falls, or other critical health conditions.

The authors in [91] proposed a system for Chikungunya diagnosis using context-aware information fusion techniques for the analysis of disease-related symptoms, including environmental condition data. The system also alerted users to disease-prone areas using their real-time location data.

Many edge intelligent networks involve different types of sensors; some are used to obtain multisource, real-time data; some are used to detect the specific events occurring; and some are used to construct the real scene of the user. A variety of different collaborative approaches may help improve the robustness of decision-making by such edge intelligent networks.

3. Classification of Information Fusion Methods at Edge

3.1. Classification of methods in MultiSource Information Fusion

In this paper, the classification method proposed by [31] is used to classify multisource information fusion into three categories according to different key technologies: estimation theory, uncertainty reasoning, intelligent computing and pattern recognition theory.

In the work based on estimation theory, an emotional analysis model was proposed in [92]. The data collected by human sensors were then integrated with other context user data, such as position, noise and emotional state (self-report). The collected data were cleaned and preprocessed in the feature layer, and statistical correlation, covariance and multivariate regression analyses were carried out. Finally, the features were extracted from the sensor data, and feature selection was used for decision fusion to establish the emotion prediction model. The accuracy of emotion prediction was high, but due to the limited number of signals, the constraints imposed by human instruments seriously affected the algorithm design. In the future, we need to aggregate data into different space segments to study the relationship between these parameters and physical position changes to improve. The authors in [93] proposed an algorithm applied to human posture recognition. The data sources were multisensor and Lora terminal nodes, which improved the feature output frequency, reduced the energy consumption of nodes and had fast convergence speed. The classification results tended to be stable, meeting the requirements of high accuracy and fewer features of posture recognition. In the experiment, it showed that the recognition rate of standing, running and jumping was higher, but in contrast, going upstairs and downstairs and walking were easily confused, which needs to be improved. The authors in [94] introduced heterogeneous complementary data sources, proposed a UWB-based algorithm and a magnetometer-based algorithm, combined with the heterogeneous data characteristics of the UWB channel and a magnetic signal, through the introduction of propagation path length and channel impulse response (CIR) eigenvalues to achieve vehicle detection. This proved the vehicle detection accuracy, reduced the difficulty of threshold selection, greatly reduced the average power consumption of WVDs, and extended the detection time service life. The above three algorithm models are applied to filtering processing technology. The authors in [29] fused logging data and seismic data through time-depth conversion to establish a visualization system of stratigraphic correlation. In the evaluation of multiscale analysis of stratigraphic uncertainty, correlation analysis of attribute differences and stratigraphic uncertainty, and uncertainty in detailed stratigraphic correlation, remarkable results were achieved. Table 2 summarizes and classifies the related work of multisource information fusion work based on estimation theory in recent years.

Table 2: Summary of multisource information fusion work based on estimation theory

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
Filter processing	Emotion analysis model [92]	Increased sensor parameter diversity	Sensor data and self-reported data	High accuracy, high robustness	Signal acquisition is restrictive

Table 2: Summary of multisource information fusion work based on estimation theory

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
	Human body gesture recognition [93]	Increase training set	Multisensor and LoRa terminal node	High characteristic output frequency, low energy consumption, fast convergence speed	Judgment accuracy needs to be improved
	Intelligent parking management system [94]	Anti-interference ability, improve robustness	Magnetic sensor, UWB channel	High accuracy and low power consumption	System integration and reliability issues
Time-space conversion	Stratigraphic comparison, geological interpretation [29]	Increased intelligence	Log data and seismic data	Reduced uncertainty	Errors exist

In the work based on uncertainty reasoning, the authors in [53] applied fuzzy mathematics theory to dynamic interval data fusion, such as weather change. The incremental fusion mechanism was a data fusion method based on fuzzy information granulation, which transformed multisource interval-valued data into trapezoidal fuzzy granulation. The dataset used was from the UCI machine learning knowledge base. Its application effectively improved the computing performance when adding or deleting multiple data sources and reduced the computing overhead. However, in many cases, there are unlabeled interval-valued data, and the problem of clustering between values has been widely studied. Therefore, the future challenge should be to study the fusion technology of multisource unlabeled interval-valued data to improve clustering effectiveness. In [95], the original information of each target was transformed into a triangular fuzzy information granule, and the information fusion method based on granular computing was an effective information fusion method using the selected information source. It helped to select the most valuable source and effectively integrates information to provide more choices for information source selection and information fusion in a multisource environment. However, only 6 datasets were tested in this paper, which have not been applied to actual scenes. The multigranularity method in [96] regarded the equivalence relation formed by all conditional attributes in each information source as a granularity by using the fuzzy mathematics theory. Then, the Q information source formed Q granularity, and the aggregation operator was constructed by a multigranularity rough set. A set of thresholds (α, β) are always found, which makes the fusion effect better than the average fusion. It can realize direct knowledge discovery without losing information. It is also practical in the case of small source spacing. In this paper, the experiment is only carried out on the dataset and is not applied to actual scenes. In the future, the heterogeneous multisource information system fusion method will be further studied. In [97], the hierarchical model (HM) proposed by possibility reasoning is combined with iterative proportional fitting (IPF) to promote the hidden Markov model (HMM). Compared with traditional IPF and recent HMM based methods, HM obviously provides the best trade-off. It can obtain the quasi-perfect marginal distribution and the exact multivariate joint distribution, while combining an infinite number of datasets. It is mainly used in the research of cities and transportation. Table 3 summarizes and classifies the related work of multisource information fusion work based on estimation theory in recent years.

Table 3: Summary of multisource information fusion work based on estimation theory

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
Fuzzy mathematical theory	Dynamic interval data fusion [53]	Improved clustering effectiveness	UCI machine learning knowledge base	Improved computing performance and less overhead	No attention is given to sources that have different attributes
	Multisource information [95]	Solve practical issues	UCI datasets	Access to effective information sources	It has not been used in practical applications
	Multisource decision information system [96]	A fusion method for heterogeneous multisource information systems	UCI datasets	Solve information loss issues	Unable to fuse heterogeneous information from multiple sources
Probable reasoning	Urban transportation [97]	Scalability, robustness	Urban and transport research subject information	Flexible, strong competitiveness, high robustness	Data format conflict

Finally, based on the theory of intelligent computing and pattern recognition, the authors in [35] applied the deep learning algorithm to the research field of intelligent refrigerators. Although some existing methods provide new possibilities for effective target recognition to a large extent, there are still some problems in recognizing some fruits with similar color, shape and quality. The data used in the experiment were from RPI (Raspberry PI) and tx13 with a camera and load cell. The accuracy of fruit recognition was substantially improved by combining multiple convolutional neural network models with weight information. The method proposed in [28] first used a random walk strategy based on a metagraph to capture semantic information. Then, the rich semantic information, structural similarity, attribute information and tag information were jointly modeled to learn information node representation in heterogeneous information networks. The experiment was carried out on the DBLP and ACM datasets, but it has not been applied to actual scenes. In the future, we will focus on the possibility that the attribute information of nodes is multimodal (such as image, text and video). The authors in [98] used a deep learning method to construct an optimization framework to describe the learning problem and obtained multilabel classification results through the weighted combination of multiple source decisions. Experiments on three real datasets showed that it is effective to use label correlation and learn consistency-based classification methods on multisource data (especially long-tailed data). Compared with other methods, this method is competitive in multilabel classification and multisource fusion. In addition to deep learning, Bayesian networks are also used for this kind of data fusion. The Bayesian network theory mentioned in [99] originated from the development of Bayesian statistics and graph theory. It is a model to describe the dependence between random variables. Additionally, it makes full use of the information resources of multiple sensors in different times and spaces, carries out detection, correlation, tracking, estimation and data fusion at multiple levels, makes full use of the advantages of each information source, combines with a Bayesian network to address incomplete and uncertain information, and completes the reliability analysis under an uncertain environment. Bayesian conditional probability is used to describe fuzzy information, and the method is applied to the process of fault notification and uncertainty analysis of multisensor wearable devices, which overcomes the fuzzy effect of fault information, improves the processing speed of faults, diagnoses wearable devices, effectively improves the accuracy of fault analysis data and the reliability of feedback information, and improves the conversion efficiency. Thus, the accuracy and efficiency of electric fieldwork are improved. Table 4 summarizes and classifies the related work of multisource information fusion work based on the theory of intelligent computation and pattern recognition in recent years.

Table 4: Summary of multisource information fusion work based on the theory of intelligent computation and pattern recognition

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
Neural network	Smart refrigerator [51]	Rich dataset	Sensor data, TX13 data	Improved accuracy	The comparative dataset is not rich enough
	Multisource information [28]	Research on multimodal attribute nodes	Bibliographic heterogeneous information networks in DBLP and ACM datasets	High scalability, the first to consider multisource heterogeneous embedded HINS	Node properties are single modal
	Label related data and long tailed according to [98]	Use interactive machine learning methods	Drug reorientation (DR), TCM syndrome diagnosis, Corel5K	High responsiveness of fusion	No graph-based algorithm is used
Bayesian network	Monitoring power plant data [99]	Establish a unified comprehensive information model	Sensor data	Improved accuracy, reliability and conversion efficiency	Need real-time monitoring

625 In summary, these three methods can improve the efficiency of multisource data fusion, and the method based on estimation theory has a great effect on data processing, especially data with noise or data that needs to be converted, which can solve the problem of information source conflict, but it has certain constraints and is only effective for some specific data. Uncertainty-based rea-

soning is suitable for decision fusion and has great flexibility. It can solve the problem of data loss and deal with dynamic data. However, it is theoretically suitable and has not been practiced. The last method based on intelligent computing and pattern recognition theory has been widely used in recent years. Neural networks and deep learning algorithm models endlessly emerge, which brings a new breakthrough to the fusion of multisource information, but it is also more complex, needs further research in the future, and has great development prospects.

3.2. Classification of methods in real-time information fusion

This paper divides the algorithms used in real-time data fusion into three categories: probability-based methods (PBMs), evidence reasoning methods (EBMs), and knowledge-based methods (KBMs).

In the work using PBMs, Suhr *et al.* [61] proposed a low-cost precise vehicle localization system that fuses a GPS, IMU, wheel speed sensor, front camera, and digital map via the particle filter. The time update step predicts the distribution of the vehicle state using the IMU and wheel speed sensor, while the measurement update step corrects the vehicle position distribution using the GPS, front camera, and digital map, which is implemented in a low-cost real-time embedded system. However, a very small amount of misdetection may also have the disadvantage of increasing the positioning error. Liu *et al.* [62] proposed a navigation system information fusion method based on innovation adaptive estimation Kalman filtering (IAE-AKF), which is also based on memory attenuation to suppress noise. Introducing the attenuation factor to increase the weight of the current value reduces the filtering influence of information fusion of data collected in the past, benefits the real-time control of the vehicle, and improves the navigation information precision. Lian *et al.* [57] proposed a real-time multiface tracking system based on a feature fusion algorithm. After feature extraction, the motion features and other features were fused to solve the problem of data association. The Kalman filter was used to predict the position and achieve the real-time target by fast calculation. Li *et al.* [63] proposed vehicle recognition based on information fusion to improve the real-time accuracy of vehicle recognition in complex traffic scenarios. A maximum likelihood estimation method was used to fuse vehicle feature waveform information, which can improve vehicle type recognition accuracy, but it cannot reduce real-time performance. However, the recognition accuracy of large vehicles was poor. Dan *et al.* [100] proposed an information fusion-based method for load identification to be applied to briges of different lengths. The vehicle position and weight information were fused, and the Gaussian mixture model (GMM) was used for moving vehicle detection to realize the identification and tracking of moving loads all over the bridge. GMM is a real-time background modeling method based on pixel statistical information. This model is widely used in the detection of moving targets in image sequences. The GMM is a real-time method for background modeling based on statistical information of pixels and is widely used in moving object detection in image sequences. However, this method is still affected in special environments such as low visibility and strong light. Table 5 summarizes and classifies the related work of real-time information fusion work based on PBM in recent years.

Table 5: Summary of real-time information fusion work based on PBM

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
Particle Filter [61]	Vehicle positioning	High computational cost and complex environment	Vehicle driving data	Low cost, reliable positioning of vehicles in complex environments	Misdetection may also increase positioning error
Adaptive Kalman Filter [62]	City road navigation [3, 62]	GPS noise components are complex and uncertain	GPS track	Improve data utilization and reduce noise impact	In some cases, the effect is mediocre

Kalman Filter [57]	Face detection [57, 65]	The scene is complex and time-consumption	Video taken at the subway station	Fast speed and high accuracy	Large number of calculations
Maximum likelihood estimation [63]	Vehicle recognition	Value for money	Urban road sensors collect data [60, 63]	High recognition accuracy, simple network deployment, low cost	Poor accuracy for large vehicles
GMM, Kalman filter [100]	Full bridge moving vehicle load	Identify the lateral and longitudinal loads of the full bridge	Video of traffic flow on the bridge	Save computing resources, reliability and accuracy	It is still affected in special environments such as low visibility and strong light

In the work using EBMs, the most commonly used Dempster-Shafer theory (DST) is composed of Shafers belief theory and Dempsters combination rule. Shafers belief theory is a hypothesis to obtain a certain degree of belief, and then DST uses the Dempsters combination rule to combine beliefs from multiple independent sources. Guo *et al.* [55] used a method based on evidence theory to fuse discriminative models and applied them to deep learning of medical image data. For real-time data and heterogeneous data problems, DST-based statistical standard fusion is comprehensively considered to obtain the final result of the model to update the system in real time. However, other types of data may have inapplicable characteristics. Boukezzoula *et al.* [58] studied a multicamera fusion strategy based on evidence theory for color object recognition. The image data were processed through a TSCC (Takagi-Sugeno fuzzy system with constant conclusions) system to provide an output indicating the detected color. The DST combination rule was used to obtain evidence of fusion, and a decision method was used to obtain the final decision about color. However, increasing the number of sources can lower the real-time performance of the detection system. Zhang *et al.* [66] proposed a novel hybrid information fusion approach that integrates the cloud model (CM), DST evidence theory and Monte Carlo (MC) simulation technique to perceive the safety risk of tunnel-induced building damage under uncertainty. Hard data and soft data were combined to monitor, analyze and evaluate the safety of existing buildings in an accurate and real-time manner. Of course, some input factors in sensitivity measurements may still have unreasonable changes with unpredictable errors. Chen *et al.* [59] developed a pedestrian detection system for multicue event information fusion. The DBF (dynamic belief fusion) algorithm composed of DST was used for information fusion to detect real-time targets and reduce the problem of inaccurate positioning. Need to ensure a balance between running time and accuracy. Table 6 summarizes and classifies the related work of real-time information fusion work based on EBM in recent years.

Table 6: Summary of real-time information fusion work based on EBM

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
D-S theory	Medical image deep learning	Data accumulation, time-consuming	Clinical image data [55]	High recognition accuracy and reliability	Other types of data may not apply
	Color object recognition [3, 58, 67]	Limited capacity for inaccurate and uncertain environments	Image data captured by the robot's camera [56, 58]	High reliability, high performance	The signal source increases, and the real-time detection performance decreases
	Monitor and evaluate the safety of buildings	Uncertainty	Building data next to the tunnel [66]	More accurate, robust, fault-tolerant	Unpredictable errors may occur in sensitivity measurement

	Pedestrian detection [59]	Low frame rate will reduce detection speed	Pedestrian dataset	Robustness, reducing inaccurate positioning problems and improving detection accuracy	Detector detection accuracy affects fusion

The use of KBMs is mostly used in machine learning neural network methods to address information fusion problems. Meng *et al.* [65] proposed a real-time estimation method of building space personnel load and an air conditioning predictive control strategy that integrates image information. An end-to-end building space personnel load dynamic estimation model was established based on a convolutional neural network. The VGG16 preprocessing model was used to extract features, and multiple loss fusion (classification, regression loss) was used to calculate the head boundary map to achieve real-time personnel occupancy load change estimates. According to the real-time change in load, the cold compensation and indoor temperature change trend were predicted, and the air-conditioning predictive control strategy was obtained. The limitation of this method is that different buildings have different scopes. Jiang *et al.* [26] implemented a real-time emotional health monitoring system through multimodal information fusion to improve the lack of single-modal emotional information and the vulnerability of various external factors, leading to low accuracy of emotion recognition. The design method of efficient emotional data collection still has certain difficulties in emotion recognition and interaction. An artificial intelligence algorithm was used to recognize and analyze the fusion of multimodal affective data, and a feature fusion layer and softmax classifier were designed in the neural network. The fusion results of multimodal affective data were obtained, which can provide real-time personalized mental health monitoring for users. Wang *et al.* [101] proposed a deep learning-based model termed the multiresolution and multisensor fusion network (MRSFN) for motor fault diagnosis. MRSFN integrates multisensor fusion and multiresolution fusion into a unified end-to-end framework and provides progressive fusion of sensor data via CNN and LSTM (to achieve multisource data fusion and time information encoding), to achieve a balance between local and global dynamics suitable for online, real-time monitoring applications. Table 7 summarizes and classifies the related work of real-time information fusion work based on KBM in recent years.

Table 7: Summary of real-time information fusion work based on KBM

Methods	Application scenarios	Challenge	Data	Advantages	Disadvantages
Convolutional neural network [65]	Personnel load and air-conditioning predictive control strategy	Great changes in personnel flow and complex environment	Image information inside the building [57, 59, 65]	Accurately estimate, reduce energy consumption	Different buildings have different scopes
Neural network	Real-time emotional health monitoring [2, 26]	The accuracy of emotion recognition is low	Collect user's voice and expression data [15, 26]	High emotion recognition accuracy, good generalization ability	Data collection still has certain difficulties in emotion recognition and interaction
Multiresolution and multisensor fusion network (MRSFN)	Motor fault diagnosis [101]	Time-consuming, global and local dynamic balance	Motor operating data	Automatically determine importance	Rely on data collected from failed machines

In summary, in the field of real-time information fusion, early research is based on probability methods, but in recent years, research has gradually focused on evidence-based reasoning and knowledge-based methods. The probability-based method introduces a probability distribution or density function to address the incompleteness of the data, which can express the dependence between random variables and establish the relationship between different datasets. The DST has the ability to process uncertain information and allows reasoning in dynamic situations. Knowledge-based methods can effectively deal with complex and multivariate data and can deal with inaccuracy and uncertainty of data through fusion. However, it is necessary to avoid the pursuit of accuracy, resulting in excessive calculations, consuming calculation time and affecting the real-time system performance. If the highest precision is always emphasized for information fusion, it will lead to too many calculations, and the calculation time may not meet requirements. Similarly, if poor accuracy is used for information fusion, although the real-time performance of the system is guaranteed, it may reduce system performance.

3.3. Classification of methods in event-driven information fusion

According to the three challenges faced by event-driven information fusion technology, the related work of event-driven data fusion is divided.

To address the validity of the event-triggered strategy, the authors in [75] proposed a multichannel decoupling event-triggered strategy. Compared with the traditional event-triggered strategy, the communication of the sensor network can be used more effectively when the communication resources are limited, but there is still room for further optimization of the event-trigger threshold. The authors in [71] designed an energy-saving information fusion strategy triggered by the detection of moving targets (such as unmanned aerial vehicles (UAVs)), in which sensor nodes cooperate to detect the presence of harmful targets, and event detection is based on sensing the presence or absence of the monitored area. Abnormal electromagnetic signals can effectively reduce energy consumption and extend network life. The authors in [102] discussed the distributed detection of noncooperative targets on WSNs. A fusion rule based on the generalized likelihood ratio test (GLRT) and Bayesian method was given. This scheme improves energy efficiency and bandwidth efficiency. The authors in [70] studied the sequential fusion estimation problem of mobile sensor node positioning based on the received signal strength requirements in mobile wireless sensor networks and proposed a sequence fusion estimation method based on filtering (SRCKF) to solve the problem in mobile wireless sensor networks.

Considering the positioning problem of mobile robots, the use of event-driven sampling methods effectively reduce the number of sampling and transmission. This reduces sampling and transmission, which can avoid network congestion and communication conflicts. Table 8 summarizes and classifies the related work of event-driven information fusion work based on the challenge of event-trigger strategy effectiveness in recent years.

Table 8: Summary of event-driven information fusion work based on the challenge of event-trigger strategy effectiveness

Method	Scenarios	Challenge	Data	Advantage	Disadvantage
Multichannel decoupling event-trigger strategy and diffusion Kalman filter algorithm [75]	Wireless sensor network	Event-trigger strategy effectiveness	Communication data between network nodes	Increased utilization of network resources	Event-trigger threshold optimization
Event detection is based on the radio signal of a moving target [71]				Reduced energy consumption and extended network life	Assume that the location of the target and sensor node is unknown
Fusion rule based on GLRT and Bayesian method [102]				Improved energy efficiency and bandwidth efficiency	Unilateral testing of harmful parameters only under the assumption that the target exists

Sequential fusion estimation of mobile sensor node location based on a new filter (SRCK-F) and received signal strength (RSS) measurements [70]				Reduced energy consumption	Did not consider long-distance transmission

To address the challenge of rapid incident response, the authors in [76] proposed an event-driven visualization mechanism. The low-level surveillance data obtained through a multimodal camera network were integrated into a smart interface. The advanced information of the camera was visualized and automatically displayed as the only important video stream corresponding to spontaneous alarms and events through a decision-making process called display switching arbitration. A new method of camera selection that considers not only objects but also events was developed. Personnel intuitively prevent the occurrence of incidents, thereby facilitating a rapid response to the incidents. The authors in [73] introduced an event-driven method using IEC 61499 function blocks, which can use real-time monitoring data of the production workshop to adapt to dynamic changes. Data from the machine tool in the workshop are collected and input by the operator with the relevant monitoring data of the machine tool schedule through the sensor. Information fusion technology consists of the analytic hierarchy process (AHP) and the DS theory of evidence. By combining the above heterogeneous information sources, the state of the machine tool can be obtained. The common goal of all of the above objectives is to generate a flexible, rapid response, adaptable and feasible process plan. The authors in [103] proposed a traffic safety information fusion algorithm based on DST. In the internet of Vehicles, when a traffic accident occurs, event-driven safety information is generated, and event-driven traffic safety information and time, location and other parameters are integrated to warn the following vehicles about dangerous states with a simple context. The algorithm improves the reliability and simultaneously reduces the immediacy of the information fusion algorithm, as well as the complexity. It also improves the efficiency of wireless resources by compressing redundant information and reduces the throughput of transmitted information. Table 9 summarizes and classifies the related work of event-driven information fusion work based on the challenge of rapid incident response in recent years.

Table 9: Summary of event-driven information fusion work based on the challenge of rapid incident response

Method	Scenarios	Challenge	Data	Advantage	Disadvantage
Event-driven visualization [76]	Large-scale intelligent video surveillance system	The rapidity of event response	Video information of the camera	Quick response to adaptive events	System performance evaluation is not comprehensive
Event-driven using IEC 61499 function blocks [73]	Industrial production workshop		Machine tool-related data	Adaptive decision-making capabilities for distributed workshop monitoring and process planning	Further testing is required in multiuser and multiprovider environments

Traffic safety information fusion algorithm based on DST [103]	IoV		Traffic safety information	Improve wireless resource efficiency and reduce the throughput of transmission information	Uncertain performance in complex traffic conditions
Fusion estimation scheme based on local estimation and CI [104]	Wireless sensor network		Communication data between network nodes	High robustness	Set the upper limit of unit sampling

To address the challenge of time-varying events, the authors [104] studied the problem of event-triggered robust fusion estimation for a class of uncertain multirate sampling data systems with random nonlinearity and colored measurement noise. The authors in [78] studied the recursive filtering problem of a class of time-varying nonlinear stochastic systems. There are event-triggered transmissions and multiple lost measurements with uncertain loss probabilities. Measurements from different sensors may be missing, and the missing probability may be uncertain. In addition, a time-varying filter was designed, and an event-triggered transmission mechanism was introduced to reduce the burden of network communication. Thus, the current measurement value is transmitted to the remote filter only when the current measurement value changes greatly compared with the previous value. The authors in [77] considered the problem of estimating the distributed state of a class of time-varying systems on sensor networks. Starting from the purpose of network resource utilization, using an event-triggered communication scheme, a set of time-varying state estimators were designed while retaining a satisfactory performance. According to the proposed scheme, the measurement on each node is sent to the estimator only when certain trigger conditions are met. While saving network computing resources, it also improves the reliability of data transmission, but the robustness is poor in more complex systems. The authors in [105] introduced an event-driven fusion model that fused the temporal relationship between events and performed the emotion recognition task of entertainment classification on the Belfast S-tory/Telling Corpus. This method does not directly fuse information of the same time range in the entire modality but it indirectly calculates the probability by accumulating shorter, detected (indicated and possibly temporal) shift events. It applies the event-driven concept to automatic emotion recognition, showing the potential of the event-driven method, which is particularly suitable for real-time applications. The proposed vector fusion implementation is only a method to correlate event detection with multimode fusion. Because vector fusion has an easy-to-understand logic and structure, it is a good starting point for analyzing event-driven fusion methods. Table 10 summarizes and classifies the related work of event-driven information fusion work based on the challenge of time-varying events in recent years.

Table 10: Summary of event-driven information fusion work based on the challenge of time-varying events

Method	Scenarios	Challenge	Data	Advantage	Disadvantage
Event-triggered time-varying filter [78]	Wireless sensor network	Time variability of the event	Communication data between network nodes	Reduce the burden of network communication	Algorithm accuracy needs to be improved
Consider event-triggered schemes in distributed state estimation [77]	Wireless sensor network		Communication data between network nodes	Save computing resources and improve data transmission reliability	Less robust in more complex systems

Event-driven fusion model (vector fusion) [105]	Emotion recognition system		Belfast storytelling corpus [106]	Improved accuracy of hedonic recognition	Lack of robustness in complex network structure

3.4. Classification of methods in context-aware information fusion

This paper divides the algorithms used in context-aware information fusion into three categories: probability-based methods (PBMs), evidence reasoning methods (EBMs), and knowledge-based methods (KBMs).

In the work using PBM algorithms, the authors in [85] proposed a context-aware, self-optimizing, and self-adaptive system for sensor data fusion based on a three-tier architecture and applied dynamic Bayesian networks (DBNs) to smart home scenarios. Bayesian algorithms allow for reliable data collection by handling data problems caused by ambient noise or hardware failures, while self-optimization allows sampling of a subset of sensors to minimize energy consumption and maximize reasoning accuracy. The authors in [86] applied DBNs to IoT-based intelligent traffic management. By integrating information, such as time, weather conditions and driving patterns, the real-time road congestion status is evaluated, and corresponding planning and scheduling are carried out. The authors in [107] applied the Markov logic network (MLN) to smart home scenarios to build voice-responsive home automation systems. MLN offers a unified theory for dealing with logical implications, uncertainty, and data loss. However, prior knowledge is needed to learn weights and structures from large quantities of data. The authors in [79] used the conditional random field (CRF) algorithm to estimate the sensor environment (with an accuracy of 98.5%) by learning the observations (readings) from nearby sensors to adjust them to the context of the IoT devices and selecting the optimal subset of sensors. Based on the simulation of smart city synthetic traces and the actual test bench, the CRF model was realized, and the relationship between sensors was verified. The abovementioned work ignored the privacy issue in context-aware information fusion. The authors in [108] proposed a privacy-preserving framework where privacy is inherently built into the solution based on onion routing and perturbation or randomization techniques. They also exploited the idea of weighted collaboration to increase the reliability and to limit the effect of noisy devices (due to sensor noise and privacy). Table 11 summarizes and classifies the related work of context-aware information fusion work based on the PBM method in recent years.

Table 11: Summary of context-aware information work based on the PBM method

Method	Scenario	Challenge	Data	Advantage	Disadvantage
Dynamic Bayesian networks (DBNs) [85, 86]	Smart home	Sensor selection, reliable data collection	Aruba dataset of the CASAS Smart Home Project	It can simultaneously save energy and keep high reasoning precision	The association and interaction between heterogeneous nodes are ignored
	ITS [86, 109]	Sensor selection, reliable data collection	Video scripts based on real travel time records	Predicts real-time congestion and suggests routing solutions by distributing alerts automatically	Need prior probability

Markov logic network [107]	Smart home	Reliable data collection	SWEET-HOME dataset	Can handle logical implications, uncertainty, and data loss	Need prior probability
Weighted average fusion	Room-level localization [108]	Reliable data collection, privacy preservation [80, 81, 87, 108]	Wi-Fi RSSI values, Cell ID, location area code (LAC), etc.	Privacy preservation via Tor network	Fixed evaluation threshold
Conditional random field (CRF) [79]	Smart city	Sensor selection, reliable data collection	Sensor readings recorded at the campus of the University of La Rochelle, France	High accuracy estimation of sensor environment (up to 98.5%)	The association and interaction between heterogeneous nodes are ignored

In the work using EBM algorithms, the most common is DST. Compared with traditional Bayesian theory, DST can assign uncertainty or ignorance to the problem, thus retaining the uncertainty context information in the whole process and extrapolating it on a dynamic basis. The authors in [110] applied DST to user activity recognition in smart home scenarios, and it improved the accuracy and reliability of context-aware information fusion. However, the probability function in DST is difficult to calculate, which limits its application. The authors in [111] used the traditional DST, combined with the fuzzy mathematics method, using the fuzzy membership function as the distribution value the of probability function in DST, which solves the key problem of establishing the distribution function model in DST and obtaining better fusion performance. The authors in [111] also avoided data leakage by data processing and real-time computing on edge devices, but this privacy protection method also needs to reduce battery consumption by reducing the cost of sensor acquisition and computing. Table 12 summarizes and classifies the related work of context-aware information fusion work based on the EBM method in recent years.

Table 12: Summary of context-aware information fusion work based on the EBM method

Method	Scenario	Challenge	Data	Advantage	Disadvantage
Dempster-Shafer theory (DST)	Smart home [84, 107]	Reliable data collection [27, 110]	UCI machine learning repository	Robust	Difficult to achieve a mass function
Fuzzy mathematics and DST	Smombie detection [111]	Privacy preservation, reliable data collection	Data collected from volunteers	Solve data uncertainty, accuracy	The heterogeneity of sensors on different phones is ignored
Hermit&Pellet reasoner	Health-IoT [83, 112]	Sensor selection [88, 89]	Care data(CD)	Fast system response	The system is highly dependent on allocated memory

The work using KBM algorithms enables the fusion center to gain data from imprecise big data, which has no need to obtain a density or distribution function. KBM algorithms include intelligent aggregation methods, machine learning, and fuzzy logic [80]. The authors in [109] introduced a distributed cooperative framework for context awareness in the internet of Vehicles. Knowledge representation and reasoning (KRR), which is a nonmonotonic reasoning method, can handle inconsistent information and false information. Although this distribution protocol is designed for vehicular ad hoc networks (VANETs), the results of knowledge fusion are applicable to multiagent systems (MASs) in a wide range of environments. The authors in [113] described a system that used environmental data collected from sensors in smart devices to define context and user preferences. Additionally, context data were fed into a context-aware decision engine for information fusion. The implementation algorithm of the decision engine was neural networks and random forest along with fuzzy logic. The system was implemented and evaluated by a practical case in a smart home, with almost no overhead or delay. To reduce data dimensions, the authors in [113] applied an extra trees classifier (ETC) feature selection algorithm to the dataset to identify the most relevant data relationships for the control variable. Neither of these efforts addressed the issue of privacy preservation. Table 13 summarizes and classifies the related work of context-aware information fusion work based on the method of KBM in recent years.

Table 13: Summary of context-aware information fusion work based on the KBM method

Method	Scenario	Challenge	Data	Advantage	Disadvantage
Knowledge representation and reasoning (KRR)	ITS	Reliable data collection	Data from NCTUns simulation engine [109]	Can resist the false event caused by the missing or inaccurate value in the input data	Semantic annotation method is relatively simple
Neural networks and random forest along with fuzzy logic	Smart home	Sensor selection	Prior knowledge data (PKD), room data (RD), user room data (URD), user commands data (UCD) [113]	Reduce dimensions without losing data relevance	System scalability is ignored

In summary, in the field of context-aware information fusion, most of the early research was based on probability, but in recent years, the research has gradually focused on DST and KBM algorithms. DST has a good effect in dealing with reliable data collection, but it is difficult to estimate the quality function by using the quality function to represent the belief distribution. It can also handle the problem of reliable data collection and optimal sensor selection, but there is not much work on the experimental verification in this kind of method. In addition, in the existing work, there is less consideration about privacy preservation, and even if there is, the traditional methods, such as anonymity and no uploading to the cloud, have more room for expansion.

4. Future Directions and Open Issues

In the past five years, information fusion technology in edge intelligence has developed rapidly and is widely used in 5G, the Internet of Things, smart cities and other fields. However, the following challenges still need to be solved in the future.

1. The first challenge involves the conflict of information sources. Data exist in various sources. To make full use of the data, it is necessary to obtain a unified form of data from multiple sources, and conflicts may arise between these sources. For example, in smart homes, it is necessary to obtain information from sensors of various household items (lighting, TV, refrigerators, audio, etc.). For the current information source conflict problem, conflict detection, entity disambiguation, entity alignment and other operations are needed, which is a future research subject.
2. The second challenge is handling information loss. When the number of sensors is large, the processing of massive monitoring data not only consumes a large number of computational resources but also blocks the entire information network, even causing information loss and ultimately lower accuracy. For example, in the internet of Vehicles, sensors are needed to collect and process traffic and environmental data. Promoting methods to

handle a wide range of input data formats is an important issue, and fusing current data formats with other types of data remains a key challenge.

3. Data backlog is another challenge to overcome. When merging updated data streams, the continuously updated data stream may have difficulty guaranteeing data quality under certain specific circumstances, making fusion invalid. In extreme scenarios, there may be too much data, making the number of calculations too large, which resulting in low fusion efficiency. As a result, the scheduling problem of the next batch occurs when the previous scheduling is not completed, causing a data backlog problem. For the communication system, the delay caused by the data backlog affects the communication performance, and the emergency may not be detected in time.
4. The next challenge is addresses performance balance. When real-time application systems have high requirements for real-time processing, if information fusion is always emphasized with the highest accuracy, no matter how fast the fusion speed is, it may not be able to meet the requirements. Similarly, if poor accuracy is used for information fusion, although the real-time performance of the system is guaranteed, it may reduce the performance of the system. Smart life requires very high data fusion accuracy, where data used for medical analysis carry personal health information. Low-precision data fusion may lead to inaccurate health alerts. Due to the real-time and rapid changes in traffic conditions in intelligent transportation, low-precision data fusion may cause positioning and navigation deviation problems.
5. The next challenge is regarding event-driven event density and trigger threshold optimization. In addition to accuracy and stability, the evaluation of sensor network performance should also consider event density and quality. At the same time, to enrich sparse events, the potential direction of future work includes and imports multiple data sources. Event-driven thresholds are an important part of event-driven strategies and are the key to triggering information fusion. It has an important impact on the per-

formance of algorithms and network models. Future work should include the optimal design of thresholds.

6. Design of fusion rules is an additional challenge to resolve. Future work will include the design and analysis of fusion rules based on sensor-based soft decisions. Different fusion rules can be used to extend the use of auxiliary information (such as the understanding of sensor node locations) at the edge of the network at the sensor.

7. Sensor selection is the next challenge to address. In the edge intelligence framework, a large number of edge devices are used to perceive data. Different sensors generate data in various formats and at different sampling rates, resulting in differences in data resolution, accuracy, and reliability. It is not wise to use all types of sensors for information fusion, and sensor selection can reduce computing costs and communication overhead. The authors in [114] mentioned that the data redundancy and transmission delay are two problems for improving network performance in the body sensor networks (BSNs). Setting up and adaptively selecting the best sensor is still a challenge.

8. In addition, privacy preservation is also a challenge. Privacy preservation is often ignored in existing work. As mentioned above, in context-aware information fusion, many application scenarios will carry too much personal information, which increases the risk of user privacy violations. Currently, smart cities are producing a considerable amount of industrial data associated with transportation, health care, business, social activities, etc. However, the industrial data collected from smart cities are often sensitive and contain partial user privacy such as spatial-temporal context information. Therefore, it is becoming necessary to secure user privacy hidden in the smart city data before these data are integrated for further mining, analyses and prediction [115]. The existing encryption algorithms and nonupload processing methods are not suitable for the requirements of timeliness and low energy consumption in a fast-changing environment. The authors in [80] suggest that in highly distributed systems, a secret-

sharing-based scheme may be the solution to this problem. The method fuses data in the cluster to reduce communication costs. More advanced solutions can continue to be explored in the future.

5. Conclusion

Edge intelligence capability will enable the development of a whole new category of applications and services. However, due to multisource heterogeneity and a large quantity of sensory data, it is necessary to improve the data processing and decision-making capacity on the edges. Hence, information fusion has become an important technique to eliminate the imperfect nature of data, optimize the quantity of data and extract useful information from widely sensed or collected data. Specifically, information fusion occurs in a vast variety of edge intelligence scenarios, including medical diagnosis, autonomous driving, and smart homes. In this paper, we reviewed four main information fusion methods to study their pros and cons. Multisource information fusion mainly focuses on the data from different sources and optimizes it to improve quality. Real-time information fusion obtains new information from a large quantity of data in a timely manner, and then the data source can finally be effectively and timely processed. Event-driven information fusion extracts effective information from the data and senses events that cause the entity's state to change. Context-aware information fusion needs to identify information that can be used to characterize the background or situation of involved entities. According to them, the edge devices contribute to a final decision or service. Information fusion in edge intelligence has been widely researched in recent years. However, it still incurs some issues and challenges, such as privacy leakage and power consumption. Based on this survey and discussion, we identify a number of open research issues and further highlight promising future research directions to guide future research toward information fusion in edge intelligence.

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- Description about the capacity of information fusion in the edge intelligence.
- Introduction about multisource information fusion for edge intelligence.
- Introduction about real-time information fusion for edge intelligence.
- Introduction about event-driven for edge intelligence.
- Introduction about context-aware information fusion for edge intelligence.

Author Statement

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Conflict of Interest

Yin Zhang, Chi Jiang, Binglei Yue, Jiafu Wan and Mohsen Guizani declare that they have no conflicts of interest.