ECIC: A Content and Context Integrated Data Acquisition Method for Artificial Internet of Things

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Abstract. The Artificial Internet of Things (AIoT) is considered to reshape future business models and provide accurate services for multi-source, heterogeneous, massive, low-value density IoT data, which is vital to deepening the application of IoT. Aiming at the existing data collection mechanism's low accuracy, limited latency performance, underutilization of edge computing resources, and neglect of user data collection context, a content and context integrated data acquisition method is proposed. First, an edge entity observation content prediction method is proposed to precisely assess the entity observation based on the edge computing. Second, a cloud context-aware approach is designed that considers the user's explicit and implicit data acquisition context to select appropriate entity data according to user preferences. Finally, an intelligent data collection mechanism that integrates edge resources and cloud resources is presented to improve the performance of AIoT data collection services. Simulation results show that the proposed method can enhance 7% of the precision and lower 16% of the delay performance in comparison with traditional methods.

Keywords: Artificial Internet of Things · Edge-cloud collaborative · Data acquisition · Context perception

1 Introduction

As the era of the Internet of Everything is approaching, the Internet of Things (IoT) and artificial intelligence (AI) are regarded as the key to reshaping future business models and even changing human living models. The integration of new technologies such as artificial intelligence, cloud computing, and edge computing is an efficient way to achieve high-level and intelligent applications of AIoT [1,2].

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Currently, there is no consensus in the academia and industry on the concept of AIoT. The AIoT has been implemented in various actual fields such as intelligent home, smart city, smart medical care, unmanned driving, and smart industrial control.

The upgrade of communication technologies just solve the interconnection problem of things. Intelligent and personalized service is the bottleneck of IoT development [3]. To this end, researchers apply cloud computing [4] technology to the Internet of Things to effectively alleviate the conflict of limited computing, communication and storage capabilities of IoT devices. However, the restricted bandwidth and ultra-long distance between devices and cloud servers, the high load, large delay, privacy leakage and other problems are brought about by the long communication link. Researchers further proposed the edge computing [5] architecture. The characteristics of edge servers close to users are able to effectively alleviate the problems of cloud computing models. However, edge computing only grasps partial data rather than all the data, and the resources of edge are relatively limited. The cloud-edge collaborative computing model can make full use of the rich communication, computing and storage re-sources of the cloud, and the advantages of the edge being close to the user and being able to respond rapidly, thus the cloud-edge collaboration model has attracted a lot of attentions of researchers [6,7]. The cloud can conduct in-depth analysis of the global data, which is suitable for non-real-time data processing scenarios; the edge server focuses on local areas and is suitable for small-scale, real-time intelligent analysis tasks and the cloud can remove its own unloadable components migrate to multiple edges or clouds to minimize service latency in parallel processing.

Data acquisition service is based on the user's submitted desired entity content to select appropriate entity data via searching in massive entity-attached sensors deployed in the AIoT, and return the matched entity data to the user [8–10]. The concept of data acquisition originated from Internet search engines which are mainly oriented to virtual information resources in the cyberspace [11,12]. The data acquisition technology can accurately match the interest information according to the user's intention, greatly reduce the unnecessary communication burden, and make the user's access to information resources more intelligent, convenient, and personalized. On-demand efficient multi-source data acquisition of AIoT is the core service content of AIoT, and it is the data base that supports AIoT third-party service applications [7]. The data acquisition function of Internet data acquisition engine is implemented by establishing a static index of virtual information resources. However, the status of physical entities is extremely dynamical, and traditional Internet data acquisition methods fail to present the accurate status information of physical entities in real time. Therefore, traditional Internet data acquisition methods perform poorly when solving the problem of data acquisition in the AIoT. How to achieve real-time and efficient data acquisition, so as to rapidly and accurately select entities that meet users' needs is a key scientific issue of great research and application value.

Currently, research on data acquisition in the AIoT is at an early stage. In [13], a data acquisition engine, WOTS2E, for semantic AIoT to discover web device resources in real time was designed. A novel type of sensor network data acquisition engine based on natural language processing and semantic Web technologies was proposed in [14]. In [15], a data acquisition framework for AIoT was presented. Furthermore, ViSAIoT was designed in [16] to provide a solution of data acquisition service via virtual sensors distributed on a wide area public cloud platform.

There are huge number of diverse sensors in the AIoT, which generate the state information of the physical world entities all the time. Therefore, data acquisition ser-vice, which selects sensor data based on their observation contents will become one of the most extensive and core services in future AIoT applications [17]. For the existing research on data acquisition mechanism, most of them ignore the communication and computing resources of edge, and concentrate all the tasks of entity state prediction in the cloud, which brings a large amount of computing load to the cloud, making the data acquisition efficiency unsatisfied. Moreover, existing entity content forecasting methods are based on shallow learning theory to predict the observation content, and select the data based on the predicted content, leading to inaccurate data acquisition results and large data acquisition delay. It was pointed out in [18] that the deployed sensors continuously generated a large amount of data about physical world entities. How to understand these data was a crucial issue. Context-aware computing would be an effective way to alleviate this problem and thus promoted the deep application of the AIoT. Context-aware computing technology [19] can filter out the required data re-sources from the AIoT massive information space by analyzing the user's preferences and the current context state. The current data acquisition mechanisms are just based on observation content to match desired sensors and neglect to consider the user's data acquisition context, which further leads to the lower accuracy and poor real-time performances of data acquisition processes.

Aiming at those above problems, an edge-cloud intelligent collaborative data acquisition mechanism, ECIC, is presented. The contributions are listed as follows.

- An Edge content prediction method is proposed. Based on the idea of edge computing and deep learning theory, a prediction method of entity observation con-tent is designed and adopted in the edge, and the temporal correlation of quantitative observation content is analyzed in depth, and the evolution trend of the quantitative observation content is sensed, thereby realizing high-precision prediction of the quantitative observation content and reducing the computing over-load of the cloud;
- A cloud context perception approach is devised. The idea of context-aware computing is introduced. Considering the user interest in terms of sensor attributes in the data acquisition context, the explicit and implicit context awareness methods are designed respectively. The explicit context allows the user to specify the sensor's attribute according to individual preferences.

For the implicit context, the user's potential preference for sensor attributes is dynamically sensed by mining the user's historical data acquisition records;
- An Intelligent data acquisition mechanism is designed. The data acquisition mechanism is presented based on the combination of content prediction and context perception methods, which integrates cloud and edge communication and computing resources to match entity data for enhancing the data acquisition ac-curacy and delay performances.

The following contents are organized as follows. Section 2 lists the related works. Section 3 proposes the edge content prediction method. Section 4 presents the cloud context perception method. Section 5 designs the intelligent data acquisition method. Section 6 verifies the proposed methods. Section 7 summarizes this paper in the end.

2 Related Works

2.1 Content-Based Data Acquisition

There are tremendous number of diverse sensors applied in the AIoT which observe the state content of the physical world entities continuously. Therefore, the selection of sensor data according to their observation contents is one of the most vital services in future AIoT applications [20]. It was pointed out in [21] that in most AIoT application scenarios, the output of sensor that senses the state of the entity is the original measurement value. Therefore, how to select the sensors associated with physical entities that meet the user's requirements based on the content of the sensor's original measurement value is a hot topic in the field of data acquisition.

In order to realize the data acquisition based on the original sensor observation content in the AIoT, a content-based data acquisition system, CSS [22], was designed and implemented. Based on fuzzy logic theory, the historical measurement information output from the sensor was utilized to construct a lightweight observation content prediction model, which estimated the probability that the observation con-tents of the sensor matched with the request, and returned the data acquisition results in descending order of matching probability. In [23], authors elaborated that in most AIoT data acquisition scenarios, users were insensitive to the content of the raw data sensed by associated sensors, and paid more attention to the advanced observation content of the sensors after fusion processing. Based on the assumption that the sensor output was advanced observation contents, a data acquisition system was designed in [23], Dyser, which adopted the existing Web architecture for the data acquisition. A predictive model for periodic conversion of perceptible sensor observation content was constructed. By calculating the probability that the sensor observation content matched with the dynamic attributes requested by the user, a set of physical entities that might match with the user request was acquired.

In [24], a time-correlated data acquisition method, CSME, was proposed, including a matching prediction approach and an ordered verification approach. The matching prediction approach was presented based on the Least Squares

Support Vector Ma-chine (LSSVM) to estimate the short-term entity state to find candidate objects by mining the time correlation between the sequence of observation content and sensing the change trend of the observation content, so that the future observation contents would be accurately predicted, and entities could be further selected based on the predicted content. The ordered verification approach was designed to verify the actual state of candidate sensors, so as to ensure the reliability of search results. In [25], a low-overhead and high-precision data acquisition mechanism, HESPM, was proposed, which designed a multi-step prediction method and ranking method. The high-accuracy entity state prediction method (HESPM) was proposed based on deep belief network (DBN) theory for accurately perceiving the dynamic evolution trend of entity state and precisely predicting the future entity state, thus the match entities would be rapidly selected according to the predicted observation content while reducing communication and computing overhead.

However, the entity content prediction method adopted by the above method adopts a shallow learning model, or the adopted deep learning model fail to accurately mine the temporal correlation information of the entity observation content. Therefore, the prediction accuracy of the observation content of the entity is limited, which further leads to the inaccuracy of the data service content provided to the user. Moreover, the above methods overlook the context state of the user, resulting in limited performance of the user's data acquisition service.

2.2 Context-Aware Computing

In [26], it was elaborated that the introduction of context-aware technology into the data acquisition issue would greatly reduce the data acquisition space, and thus fast found the subset of entities that were most relevant to users' needs. The current context-aware technology in the IoT was summarized in [27], which indicated that the context-aware technology effectively improved the efficiency of data acquisition. Thus a context-aware data acquisition, selection and ranking model, CASSARAM, was designed in [28] to solve the problem of selecting the most relevant sensor subset from massive sensors with same property. In [29], a hypergraph that represented the context information of human-object interaction was constructed, and then a data acquisition method for the IoT, ThingsNavi, was proposed. Given a target entity, other related entities could be searched by mining multi-dimensional context information of human-object interaction. However, it focuses on searching for similar entities, not the state-given data acquisition described above. Authors discussed in [30] that existing context-aware methods neglected to take the intrinsic properties of sensors into consideration. According to sensor semantic overlay networks (SSONs), a meta-heuristic method was presented to raise the efficiency of context aware method. A hierarchical context model was designed and implemented in [31]. Based on the ontology technology, a hierarchical semantic model describing the physical characteristics and contextual relationships of IoT entities was presented, and a Hidden Markov model of con-text was established, combined with the daily habits of users, behavior models, and geographical location, etc.

At present, in the research of data acquisition mechanism based on observation content, most of the methods neglect the edge resources, adopt the shallow learning models, and fails to consider the context factors, severely affecting the data acquisition precision and delay performances of data acquisition. For solving the above problems, ECIC data acquisition mechanism is proposed in this paper.

3 Edge Content Prediction Method

As mentioned above, traversing all edge servers and entities to locate the required entity content will bring huge communication overhead. Thus we adopt content prediction method to match candidate entities as detailed in Sect. 3. However, concentrating all physical observation content prediction tasks in the cloud will bring serious computing overhead to the cloud and waste computing resources in the edge. Besides, most existing entity content assessing algorithms are derived from shallow learning methods, whose precisions are relatively low, resulting in poor accuracy per-formance for data acquisition. Based on the idea of edge computing [32] and deep learning [33], we design an entity content edge prediction method based on GRU (Gate Recurrent Unit) [34], via constructing an observation content prediction model in the edge, to analyze the temporal correlations of quantitative observations in depth, and then perceive the evolutionary trend of quantitative observations, thereby realizing high-precision content prediction and reducing the overhead of cloud.

GRU is one of the many variants of LSTM that is very effective. It has a simpler structure than LSTM network and works well. Whereas in GRU, there are only two gates: update gate and reset gate. The deep non-linear structure of GRU owns a strong ability of approximating complex functions, which can solve the long-term learning problem of relying on information and has high prediction accuracy for quantitative time series data.

Due to the time evolution characteristics of observation data, the observation data prediction model designed in this paper is shown in Fig. 1 below, which is a convolutional network that deforms one-dimensional convolution so that it can deal with time series problems. The model adopts a one-dimensional fully convolutional net-work structure where each hidden layer length is identical to that of the input layer, and a zero-padding length is added to maintain the relationship between the subsequent layer and the previous layer, so that the output generated by the network is the same as the input length. In addition, causal convolution is added, and the output of the t period is only related to the elements of the current time and the elements before the period, so as to ensure that historical information or future data will not be missed in the prediction process.

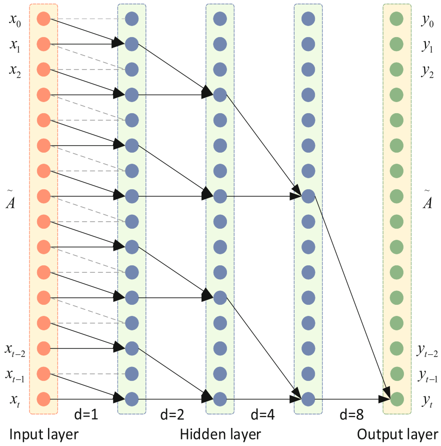

Fig. 1. Data prediction model based on GRU

In general, the observed data is a discrete series, and the predicted value is the value predicted at a certain time in the future using the stored historical data. In the data service system, the content of the observed data at a specific moment is defined as m_t. The historical observation data sequence before time $t+1$ is $M = (m_1, m_2, ..., m_t)$. Use a GRU neural network to predict observations at time $t + 1$.

a. Reset gate.

Send the last observed data h_{t-1}, and the current time input m_t to reset gate for deciding which one of the historical information should discard.

$$r_t = \sigma(W_r \cdot [h_{t-1}, m_t] + b_r), \tag{1}$$

where r_t is the output of the reset gate, W_r is the weight of the reset gate, and b_r is the offset term of the reset gate. Activation function is $\sigma = 1/(e^{-x})$.

b. Update gate.

The last state content h_{t-1}, and the current time input m_t are connected to the update gate to determine which information will be updated last time.

The update stage is

$$Z_t = \sigma(W_z \cdot [h_{t-1}, m_t] + b_Z), \tag{2}$$

Among them, Z_t, W_Z, b_Z respectively are the output, weight, and offset of the update gate.

c. Candidate stage.

Apply activation functions $tanh(*)$ and m_t to generate candidate states $\widetilde{h_t}$ and threshold them down to [-1,1] as

$$\widetilde{h_t} = tanh(W_h \cdot [r_{t-1,m_t}] + b_h), \tag{3}$$

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \tag{4}$$

d. Current state.

Discard h_{t-1} and keep $\widetilde{h_t}$ to generate new state content h_t.

$$h_t = (1 - Z_t) * h_{t-1} + Z_t * \widetilde{h_t}, \tag{5}$$

e. Spatiotemporal feature.

Through sigmoid function activation, the time-dependent character of the task sequence is extracted. The extracted temporal features are considered as the input into support vector regression for prediction, and the final predicted value is computed.

$$y_t = \sigma(W_0 \cdot h_t), \tag{6}$$

$$f(m) = \sum_{t}^{t-1} (\alpha_t^* - \alpha_i)\mathrm{k}(m_i, m) + b, \tag{7}$$

4 Cloud Context Perception Method

Perceiving the data acquisition context of users in the cloud can better provide users with excellent data acquisition experience and improve data acquisition accuracy. The entity-attached sensor owns diverse attribute functions, such as accuracy, power, security, response time, etc. Different users have diversified preferences for them, even the same user has diverse preferences in various data acquisition scenarios. To accurately sense the change of the user's data acquisition context, we first design an explicit context aware method. Before the user selects the entity, the attribute preferences are first explicitly specified by the user. Then, for perceiving the change of the user's data acquisition context, we further propose an implicit context aware method. By mining the user's historical data acquisition behavior, the user's dynamic preferences towards the sensor attributes is accurately perceived, then the matched results can be further found as described in Sect. 3.

4.1 Explicit Context Aware

The user's preference for the multi-dimensional properties of the sensor reflects the evolution of the data acquisition context. In this subsection, we establish a weighted vector space model for the multi-dimensional attributes of sensors in the cloud. Users manually set the multi-dimensional attributes of sensors according to users' needs.

The user data acquisition interface provides all or part of the sensor's attribute in-formation, and the user can customize the weight of different attribute types according to personal preferences, as shown in Fig. 2. Assume the list of sensor properties is $P = [p_1, p_2, ..., p_n]$ which defines various attributes of sensor, such as accuracy, power, security, response time, etc. p_i represents the $i - th$ attribute of sensor, $i = 1, 2, ..., n$. The weight vector $\omega = [\omega_1, \omega_2, ..., \omega_n]$ is the user's preference for various attributes where ω_i is the user's preference value for the $i - th$ attribute, $\sum_n^{t-1} \omega_i = 1$. Users can freely assign the weight of each attribute.

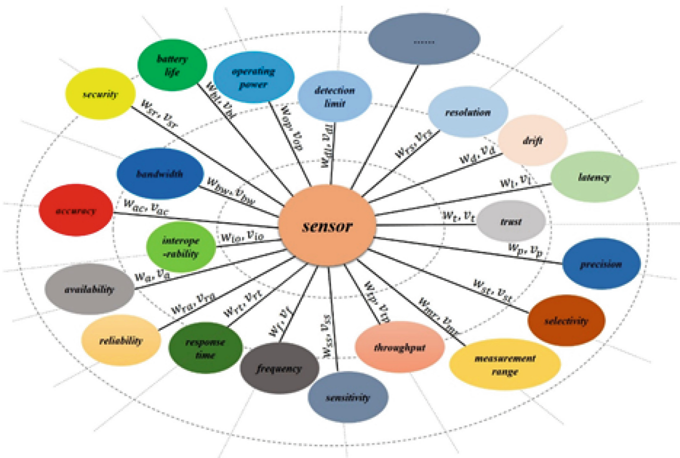

Fig. 2. Data prediction model based on GRU.

After the user defines the preferences and weights for sensor attributes, the cloud needs to determine the degree to which the sensors meet the requirements of the user's data acquisition context based on the actual capabilities of the sensor for each at-tribute. It is assumed that the value of each attribute of the sensor m is defined as $V^m = [v_1^m, v_2^m, ..., v_n^m]$ where v_t^m is the $i - th$ attribute value of sensor m. Due to the various attribute types of sensors, the dimension of each attribute is quite different, and it is impossible to judge the degree to which they match with user needs based on the value of the attribute. In this subsection, the Z-score algorithm is adopted to normalize the sensor attribute values, and the attribute values of different dimensions are converted into a unified metric Z-score value for comparison, which is defined as

$$\mu = \frac{\sum_{m-1}^{n}\sum_{i-1}^{N} v_i^m}{N \times n}, \tag{8}$$

$$\sigma = \sqrt{\frac{1}{N \times n}\sum_{m-1}^{n}\sum_{i-1}^{N}(v_i^m - \mu)^2}, \tag{9}$$

$$\overline{v}_i^m = \frac{v_i^m - \mu}{\sigma}, m = 1, 2, ..., N, i = 1, 2, ..., n, \tag{10}$$

where N is the number of sensors, μ is the average of all sensor attribute values, σ is the standard deviation of all sensor attribute values, and $\overline{v}_i^m$ is the normalized value of the $i - th$ attribute of sensor m.

4.2 Implicit Context Aware

Explicit context defines the user's relatively fixed preference for the sensor attributes. However, since the user needs to manually set the sensor's attribute preference list, which affects the user's data acquisition experience. Besides, the user's preference for the sensor will change with the data acquisition task varying. Therefore, in this subsection we further design implicit context aware method for users' potential inter-est preferences for sensors.

The implicit user interest is mainly obtained by systematically mining the interrelationships between the user's context information, behavior information, content in-formation, thereby making up for the weakness of the explicit interest information that cannot reflect the user's immediacy and dynamic characteristics. Obtaining implicit information is inseparable from the user's context information, that is, request context, environmental context, device context, etc. User behavior and operations are the key to directly reflecting user interests. To calculate the user's implicit interest preference, it is necessary to mine effective information from the user's context that affects the user's behavior and the specific content accessed, and establish an effective implicit user interest model to better reflect the user's personalized preference.

The data acquisition task and the behavior action rely on the user's interest, the core is to reflect the user's data acquisition needs during a specific period, which implicitly indicates the user's interest. Define the set $A = (A_1, A_2, ..., A_n)$ as all the behavioral characteristics of the user. The user behavior contains many aspects, such as the accessed sensor attributes, the accessed frequency, and the length of accessing time.

In the user's historical data acquisition behavior, the common attribute characteristics of all sensing devices that provide users with data acquisition services are the most direct reflection of user interests, and relatively more important attributes should be given higher weight values. The user's individual preference is defined as the user's request probability distribution for data, and the user personalized preference aware model is designed according to the idea of deep learning to analyze the user's individual needs. Define

$q_{u_n} = (q_{f_1,u_n}, ..., q_{f_k,u_n}, ..., q_{f_K,u_n})$ as the probability distribution of the $n-th$ user request, where q_{f_k,u_n} denotes the probability that the $n-th$ user needs the $k-th$ data item, $\sum_{k-1}^{K} q_{f_k,u_n} = 1$, $q_{f_k,u_n} \in [0, 1]$, $1 \leq k \leq K$, $1 \leq n \leq N$. Denote $Q = (q_{f_k,u_n})^{N \times K}$ as the user's preference matrix, the model design and user implicit preference analysis are as follows.

a. Implicit preference model.

Condition Restricted Boltzmann Machine (CRBM) is often used in the field of recommendation system, which adds comment and uncomment behavior information on the basis of restricted Boltzmann machine as $r \in \{0, 1\}^K$ (0 means not commented, 1 means commented). And through the reconstruction of the user's rating data, the implicit information of the user is learned, and the user's predicted rating for the unrated items is obtained, so as to realize the personalized content recommendation, which is suitable for the analysis of the user's potential demand.

In this paper, a user implicit preference perception model is designed in combination with CRBM, and the user's scoring of the acquired data is taken as the user's preference for the content. The higher the preference, the larger the corresponding request probability. Combined with CRBM, a user implicit preference perception model (IP2M) for data collaborative filtering is designed, which predicts the rating of unrequested data according to the user's historical rating information. Each softmax neuron in the visible layer of IP2M is directly related with a user's rating of the data. Assuming that there are a total of N users, of which there are users who have comments on the data, then use softmax neurons and missing neurons to construct the visible layer of IP2M. The IP2M network structure is defined as presented in Fig. 3 below.

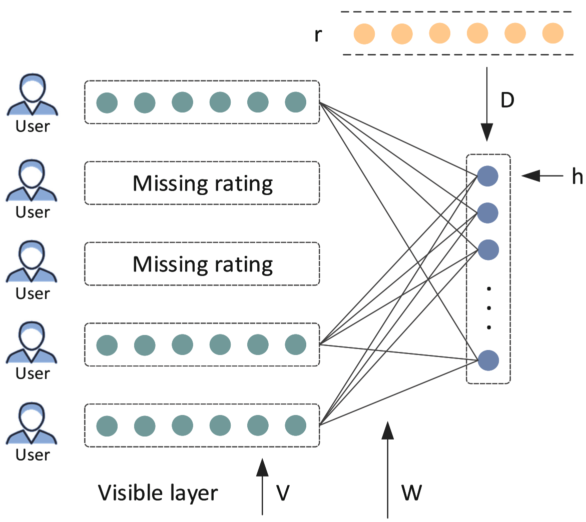

Fig. 3. The network structure of the IP2M model.

b. Implicit preference analysis.

Define $G_{N\times K}$ as the historical rating information of a user for a certain type of data. According to the historical scores, based on IP2M, predict the score of the $n-th$ user on the $k-th$ data, and finally get the reconstructed user's score on all data. The predicted score $\hat{x}_{n,k}$ is the user's preference degree towards the given data. The higher the score, the greater the user's preference for the data and the higher the request probability.

Considering that the same user usually does not request the requested data again, according to the historical score records, reset the user's requested data $\hat{x}_{n,k}$ in the re-constructed preference matrix to 0, that is

$$x_{n,k} = \begin{cases} \hat{x}_{n,k}, & \text{not requested} \\ 0, & \text{requested} \end{cases}, \tag{11}$$

According to $x_{n,k}$, the interested probability of the $m-th$ user towards the $k-th$ data, q_{f_k,u_n}, can be assessed, which is the ratio of the preference of user u_n for the data f_k to the sum of all data preferences. Finally, we can obtain the context score of user m for the sensor attributes $Context(m)$.

$$q_{f_i,u_m} = \frac{x_{m,k}}{\sum_{k=1}^{K} x_{m,k}}, \tag{12}$$

$$\text{Context}(m) = \begin{cases} \sum_{i=1}^{n} \omega_i p_i \bar{v}_i^m, & \text{if explicit} \\ \sum_{i=1}^{\phi} \omega_i p_i' q_{f_i,u_m}, & \text{if implicit} \end{cases} \tag{13}$$

5 Intelligent Data Acquisition Method

5.1 System Model

Physical entities in the AIoT own strong dynamic state-varying characteristics, thus traditional Internet data acquisition technologies are inapplicable. Existing data acquisition mechanisms need to traverse entities when performing data acquisition tasks in response to user data acquisition requests, which lead to lower selection accuracy and higher latency. In the latest research results, the prediction value of the entity observation content is stored in the database in advance, and the content-based data acquisition is performed based on the pre-stored prediction contents for effectively in-creasing the accuracy of data acquisition. However, the existing entity observation content prediction methods are concentrated on the cloud to execute, which brings serious computing overhead to the cloud. Besides, current content prediction algorithms are based on shallow learning models which have limited content prediction accuracy. Moreover, the adaptability of the entity to the current data acquisition context is not taken into account when performing the data acquisition task, which further results in the unsatisfied performances of data acquisition precision and time convergence. Targeting at this issue, an intelligent data acquisition method is designed which

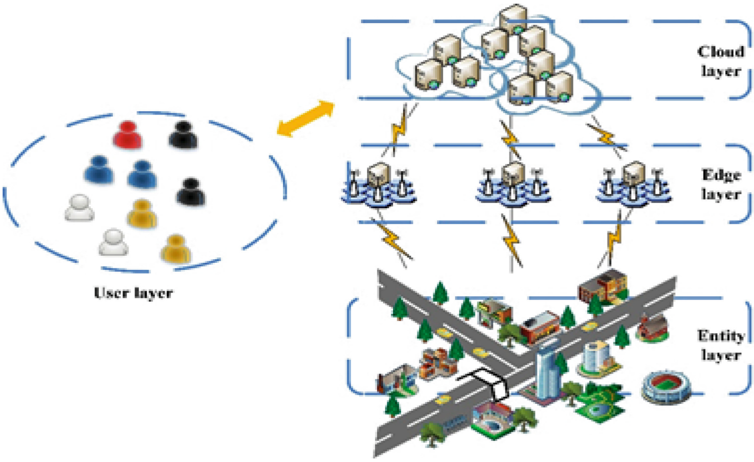

Fig. 4. System architecture.

is based on the idea of edge cloud collaboration and the deep learning theory and fully considers the data acquisition context.

As can be seen in Fig. 4, the data acquisition system is formed by cloud layer, edge layer, entity layer, and the user layer. The cloud layer consists of many cloud servers rich in communication, computing and storage resources. It responds to the user's data acquisition task request and perceiving the user's data acquisition context. The cloud server manages edge servers and interact with edge servers for entity con-tent status information. The edge layer is composed of a large number of edge servers. There are many deployment methods for edge servers, such as geographic location and resource distribution, which is not the focus of this paper. Therefore, we only assume that the edge server is deployed according to geographical location, and each edge server only covers a certain geographical area. Edge servers are only responsible for managing smart entities within their coverage and run the proposed content prediction method for entity content predicting. The entity layer is formed by a large number of physical world entities. Every intelligent entity in the physical world is associated with a sensor, and the attached sensor periodically collects its state data and transmits the observation content to the edge server.

6 Simulation Verification and Analysis

In this paper, we use the real-world dataset IntelLab [36] and NOAA [37] to verify the effectiveness of the proposed ECIC via comparing with the aforementioned mechanisms, CSME [24], HESPM [25], and CASSARAM [28]. IntelLab dataset is composed of the temperature and humidity data observed by 52 sensors and the NOAA dataset includes 98 sensors that sense the water level, water temperature, and other data along the North American coastline. We randomly choose the temperature and humidity data of 45 sensors in IntelLab and select the water level and water temperature data from 80 stations in NOAA. The main comparison performance indicators are the accuracy and delay of data acquisition. The range of sensor observation content is $[a, b]$ which is randomly selected within the interval $[x_{Min}, x_{Max}]$ where x_{Min} and x_{Max} respectively represents the minimum value and maximum value observed by all sensors. The observation period of IntelLab is 20 min and that of NOAA is 60 min. The time when the user initiates the data acquisition request for the sensing service is randomly generated. The simulation software environment is Matlab R2019a. The operating platform is ThinkPad X1 Carbon 2019 with CPU i5-10210U, memory LPDDR3 8GB, and hard disk 512G PCIe SSD. All the simulation results are average values after 100 runs. The prediction step size for entity observations is from 1 to 10. Simulation verifications are based on results within 10 days.

6.1 Content Prediction Performance Validations

Here the MAPE(Mean Absolute Percentage Error) is introduced to validate the precision of the proposed method, which is defined as

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{\hat{f}(m) - f(m)}{f(m)} \right|}{n} \times 100 \tag{14}$$

where $\hat{f}(m)$ is the predicted value, $f(m)$ denotes the actual value. In Fig. 5, with the rise of the predictive step, the MAPE values of ECIC, CSME, and HESPM, gradually increase, indicating that the growing predictive steps lower the prediction accuracy of the three methods. This is because with the expansion of the predictive step, the prediction errors of the three gradually accumulate, causing the prediction errors of the sensor observation content to gradually enlarge. It is also obvious in Fig. 5 that compared with CSME and HESPM, the ECIC can reduce MAPE by about 15% and 27%, respectively.

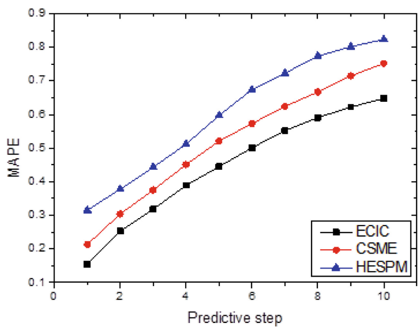

Fig. 5. Validations of prediction accuracy at different predictive steps.

6.2 Context Aware Performance Simulations

As shown in Fig. 6, with the expansion of the query range, the accuracy of data acquisition for ECIC with context, ECIC without context, and CASSARAM is gradu-ally improved. This is due to the reason that as the expansion of the query range, users are becoming less sensitive to the errors of the sensor's observations, which eventually leads to an increasing number of sensors that meet user needs. It can also be found from Fig. 8 that compared with CASSARAM, the proposed ECIC can achieve better data acquisition accuracy in consideration of the data acquisition context. In addition, considering the data acquisition context ECIC with context can improve the selection accuracy by 9% and 13%, respectively.

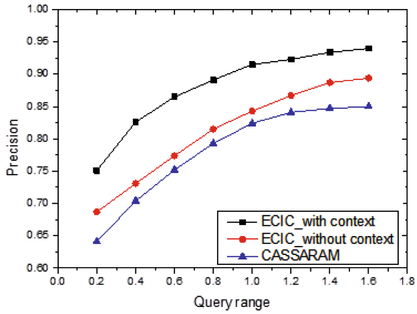

Fig. 6. Validations of prediction accuracy at different predictive steps.

As shown in Fig. 6, the data acquisition delays of the three methods at different simulation time tend to be stable. This is because the three methods are stable in the prediction performance of sensor observations. Therefore, the data acquisition process can rapidly converge and the performance tends to be stable. From Fig. 6 we also find that ECIC_with context can enhance the latency performance by 16% and 22% respectively compared with the other two. It is because ECIC_with context takes into account the user's explicit and implicit data acquisition context factors, and can fast converge when selecting sensors that provide sensing services.

6.3 Data Acquisition Mechanism Verifications

Figure 7 shows the verification results on data acquisition accuracy of ECIC, CSME, and HESPM under different query range. With the expansion of the query range, the selection accuracy of the three gradually increases. This is because the accuracy of data acquisition increases with the query range increasing, which becomes less sensitive to the selection errors. From Fig. 7, we also deduce that compared with CSME and HESPM, ECIC can improve the accuracy of data acquisition by about 7% and 12%, respectively.

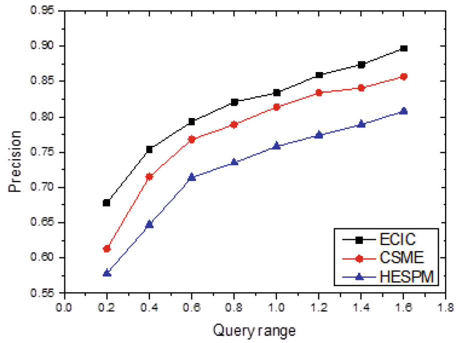

Fig. 7. Verifications on accuracy performances under different query range.

In Fig. 8, we find that with the increase of the query range, the delays of the three mechanisms are roughly stable, manifesting that the prediction accuracy of the three mechanisms towards the observation contents has stable characteristics. Besides, all the three consider the user's data acquisition context to select sensors, so that the data acquisition process can converge fast and smoothly. We can also find in Fig. 8 that the proposed ECIC mechanism can reduce the average selection delay by about 16% and 21%, respectively, in comparison with CSME and HESPM.

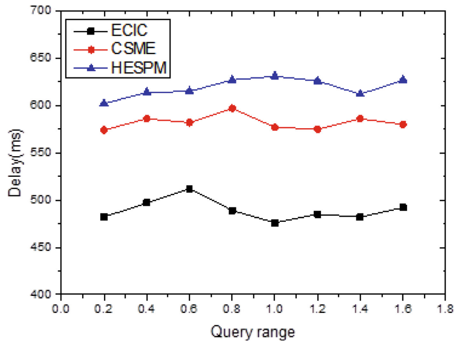

Fig. 8. Verifications on delay performances under different query range.

7 Conclusion

A content and context joint perception data acquisition mechanism is proposed in this paper, including edge content prediction method and cloud context perception method, so as to enhance the efficiency of data acquisition service. Validation results present the rationality of the proposed mechanism. In the future, it is planned to further study the sensing service incentive mechanism in the field of data acquisition service, through rewarding the sensing services and punishing the malicious behaviors, thereby promoting the deep applications of data acquisition service.

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