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# IoT Compressed Perception and Information Interaction Technology in Intelligent Transportation Layout

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This paper provides an in-depth analysis and application of the Internet of Things (IoT) compressed perception and information interaction technology to intelligent transportation layout, and builds a group intelligence-based traffic management system for event collection and reporting, which significantly shortens the response time of traffic management servers and reduces the communication overhead. Secondly, the real-time traffic management problem is modelled as an optimization problem, taking both global goals and individual utility into account. Finally, a delay-sensitive routing algorithm is proposed to shorten the transmission delay. The algorithm significantly reduces the response time of the system while ensuring efficient message transmission. A dynamic computational task offloading mechanism for efficient data distribution is proposed. This mechanism is the first in existing research to elaborate on the design of in-vehicle fog computing systems. This paper details how to scale the cloud infrastructure using docked and moving vehicles as fog nodes, and optimally models the system task scheduling, using a low-complexity approximation method to solve the optimization problem. The algorithm not only improves the resource utilization of the system and reduces the installation and maintenance cost of fog nodes, but also ensures the task latency constraint. Based on the Kronecker joint observation matrix optimization model, an optimal Kronecker spatiotemporal joint observation matrix solution method is designed, which can minimize the intercorrelation between the observation matrix and sparse bases, and reduce the autocorrelation of the observation matrix so that the matrix can be adapted to a variety of real-life scenarios, to further improve the performance of the Kronecker spatiotemporal joint observation matrix.

Keywords: Internet of Things, compressed perception, information interaction technology, intelligent transportation layout, applications

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## 1. INTRODUCTION

With the construction of smart cities and intelligent traffic management systems, telematics has become a hot research topic [1]. An efficient data distribution mechanism is the basis for smart travel and in-vehicle social networking based on telematics [2]. The goal of an efficient data distribution mechanism is to minimize the transmission delay and maximize the effective throughput of the network to ensure the response time and data transmission efficiency of the system [3]. However, the high dynamics, large scale, and heterogeneity of telematics pose a great challenge to the efficiency of the data distribution mechanism of telematics [4]. In this paper, an in-depth study on efficient data distribution in telematics is carried out using the techniques of stochastic process theory and analysis, network optimization, queuing theory, game theory, elliptic encryption, and secure multi-party computing in terms of four aspects: real-time data transmission, efficient execution of computing tasks, user privacy security, and network energy utilization effectiveness [5]. The research contents include delay-sensitive data transmission, dynamic computing task offloading for efficient data distribution, privacy protection inefficient data distribution, and energy management for efficient data distribution [6]. The first study ensures the timeliness of efficient data transfer, while the remaining three studies reduce the impact of computational resource constraints, power limitations, and security risks in the network on the performance of efficient data distribution

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algorithms [7]. This paper firstly describes the background and significance of this research, then examines the development status of related research in telematics in China and abroad, and finally introduces the research content, innovation points, and organization of this paper [8]. Two factors are driving the rapid development of telematics; it is the urgent need to improve the safety and efficiency of road traffic management systems [9]. As urbanization continues to accelerate, the number of vehicles in cities is increasing dramatically, leading to traffic issues such as traffic congestion and accidents, environmental pollution and damage, and significant economic costs [10]. In the comprehensive interoperability phase, the data collected is delivered safely and efficiently in real time through a variety of interoperable communication network channels (e.g., industrial gateways, short-range wireless communication, low-power WAN and OPT-UA, etc.) to integrate common information technology and industry characteristics. The study of solutions related to data processing for industrial IoT can be broadly divided into three categories [11]. The first category is the study of group sampling of data, which includes clustering of perceptual nodes or industrial nodes before data sampling, which helps to determine the spatio-temporal correlation between intelligent perceptual data [12]; the second category is the study of how to select and optimize the observation matrix during data compression, a suitable observation matrix can often make the data reconstruction to achieve high accuracy [13]; the third category is the study of data reconstruction methods. Many existing reconstruction algorithms such as SP, OMP, etc. can recover the original data to some extent [14].

The designs of many previous messaging mechanisms do not take into account the subject matter of different telematic transmissions, and ignore user-related information [15]. The definition of a message depends only on its natural characteristics, such as message size and lifetime [16]. Therefore, in such transmission mechanisms, all vehicles are considered as transmission targets [17]. However, current telematics-based applications are mainly used to meet the comfort and entertainment requirements of users. Hence, users expect to receive message content that matches their interests and can be of benefit to them, not messages that are irrelevant and of no interest [18]. The transmission of messages in telematics must be tagged with message content so that pertinent messages can be transmitted to users with different interests. Some data transmission mechanisms, such as the approach reported in the literature [19], are broadcast-based. These mechanisms are designed to use social communication to achieve efficient use of network resources. Blind transmission mechanisms are efficient for the use of network resources, but not efficient for users. This is because social relationships are often used in the blind transmission to speed up the transmission process by finding suitable relay nodes to improve transmission efficiency and reduce latency [20]. Also, it can reduce the use of spectrum resources by decreasing the number of transmission nodes. The interaction and data sharing between nodes are done once; i.e., there is no neighbour discovery and interest exchange process [21]. This scheme uses social associations between vehicles to select the most appropriate transmission nodes. The main disadvantage of blind transmission is that it ignores the individual user's preferences. Although content distribution techniques can distribute content to many users, the transmitted content is not necessarily useful to all users and is often ignored by them. For example, when a user receives a message, s/he can either retain or ignore the message depending on its subject matter [22].

To address the reality that the amount of data in industrial IoT is increasing dramatically, and taking into consideration the limited processing capacity of each node device (such as sensing nodes, industrial nodes, fog nodes, etc.), in this paper, we investigate ways to process big data efficiently, including cluster mechanism research, observation matrix design optimization, dictionary training, and data correlation mining. In this paper, we examine the current research status in China and abroad, address the shortcomings of other data compression schemes, and propose a performance-improving approach to reduce the amount of data transmission and energy consumption of industrial nodes in the network. The IoT architecture is studied in-depth, and a k-means-based clustering algorithm is developed to drill down the spatial correlation between perceptual data. This mechanism can recover the original data from the compressed data with high accuracy and has greater reconstruction accuracy under the same compression ratio compared with other related compression schemes. The mechanism adaptively constructs a joint Kronecker observation matrix optimization problem and investigates an efficient solution algorithm to obtain the optimal value to ensure the data accuracy for industrial applications. This innovation responds effectively to the current big data explosion and achieves better compression in the industrial Internet of Things.

## 2. IOT COMPRESSED PERCEPTION AND INFORMATION INTERACTION TECHNOLOGY IN INTELLIGENT TRANSPORTATION LAYOUT ANALYSIS AND DESIGN

### 2.1 Compressed Aware Design for the Internet of Things

In consideration of the security necessary for the smart future, it is essential to deploy a fog network at the network edge [23]. The most direct consequence of motion image ingestion is that it increases the difficulty of obtaining accurate information about the three-dimensional posture of the subjects, decreases the accuracy of subsequent three-dimensional reconstructions and the accuracy of system input data, and can lead to errors in system feedback that affect the user's actual experience. Therefore, the pre-processing of fuzzy images becomes one of the most basic and critical parts of the whole virtual display system. The image-blurring phenomenon is caused by the convolution between a blurred core and the original clear image. A simple way to remove the blur is to estimate a single fixed blurred kernel on the image, assuming that the image is uniformly blurred, and this single fixed kernel can be eliminated using the inverse convolution technique. However, there is no single fixed fuzzy kernel for image acquisition

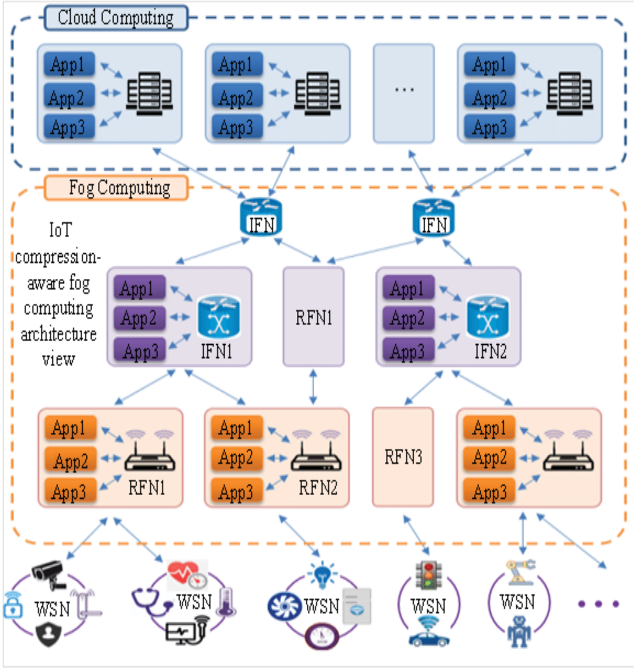

**Figure 1** IoT compression-Aware fog Computing Architecture View.

and motion analysis, and the complexity of the participants' motions and the camera shake will produce a large number of different fuzzy kernels in different parts of the image, resulting in a non-uniform doubly complex fuzzy image. To deal with this problem, in this this paper, we propose a method for accurately estimating the non-uniform blurring kernels by exploiting the sparsity on the gradient of clear images, and calculating and reconstructing one fixed blurring kernel after the actuarial calculation by the inverse convolution method respectively in the corresponding framework, so as to obtain a better reconstruction of the image. The method does not require each parameter to be adjusted and calculated, and can be better adapted to the image processing of different motion patterns and different lighting environments as shown in Figure 1.

First, the pre-processed image is used to perform operator detection of local pole position, scale, and rotation invariant feature points by the scale invariant feature transformation method; second, the image is detected by means of the nearest neighbor matching algorithm. The matching metric is the Euclidean distance between feature points; third, to eliminate false matches due to nearest match two, the algorithm is used to enhance the consistency of random samples; fourth, the method is used to filter data from 2D information to obtain a 3D point cloud structure, and the matching point pairs between multiple images are used to estimate the parameters of the topological camera to obtain the final three-dimensional structure.

Fog computing architectures enable network tasks to be processed and storage services to be provided at the fog node, and facilitate the dynamic transfer of data across the cloud and IoT continuum. However, the interface between fog and cloud, as well as other factors or user interactions, must improve service flexibility and provide dynamic relocation services by facilitating the computational, storage, and control functions between these different entities. The architecture supports fog end-user evaluation of fog computing services and enables effective QoS management. The fog-to-cloud interface is mandatory as it supports fog-cloud and cloud-mist collaboration to provide reliable, high-quality services [24]. In addition, the platform should be supported by more hardware including a coaching system, VR motion capture and capture system, VR multi-directional motion platform, VR image workstation, VR physiological data acquisition system, data server, and head-mounted presentation equipment – all of which are hardware devices that need to be improved. In addition to the existing sensors and wearable devices, some more realistic facilities also need to be improved gradually. Nowadays, many people still have 3D vertigo, while 'normal' people cannot wear these devices for too long, so the latency in the virtual environment does not match well with the color and eyes. So, in the modeling and environment collection and construction, this has become a key point in the construction of the training platform. In the platform, the coaches should have the functions of command, training, evaluation, contingency handling, data collection, environment change and tactical arrangement. They should be able to detect and evaluate the psychological and physical state of the players and organise an appropriate training program. They can change the training environment, allow the players to adapt to the conditions, and enable them to play and train in different environments.

Suppose we have a signal $X$ of length $N$, and we use a base to make the signal $X$ sparse.

$$X = \sum_{i=1}^{M} \beta_i \chi_i \psi_i \tag{1}$$

To observe X, the signal X is projected using a matrix of CS to obtain the observation vector Y:

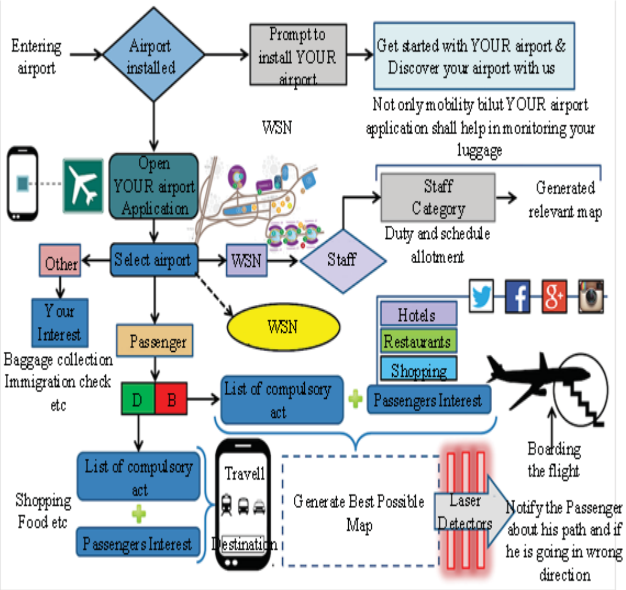

**Figure 2** All-in-One Workflow.

$$Y = \prod_{x}^{N} \phi_x \psi \theta = A^{CS} \theta \tag{2}$$

$$A^{CS} = \operatorname{argmax} \|\theta\|_i^j \tag{3}$$

To encourage vehicles to spread messages, we construct a local optimization goal for them. From a social network perspective, all vehicles in the cluster want to maximize their utility by reporting events to the traffic management server. After the cluster head collects all the messages from the cluster, it can create an accurate message. Thus, the local optimization goal can be formulated.

$$\max U_i^j = \max \sum_{i=1,j=1}^{N_C} U_i^{i*j} \tag{4}$$

If a cluster head node uploads a useful message before the traffic management server acts, then all vehicles in the cluster will be rewarded. The utility U of a cluster is related to the reward received for uploading the message, the size and cost of the uploaded message, and the upload delay. This is because they determine the timeliness of the server response and the utility of the vehicles. The server's reward is the main factor that affects the cluster's utility G, while the other three factors affect the cluster's upload policy, and all four-network metrics are positively correlated with G. The cluster's utility M is based on the number of messages received, the size of the uploaded message, and the cost of the upload. The utility M of a cluster is calculated based on the server's reward and upload cost by the following formula.

$$U_i^j = Y_i(i, j) \cdot (1 - e^{-x_m x_m} \Delta t, \theta) \tag{5}$$

Vehicles can upload information to the traffic management server in two ways, either directly through the roadside unit or through the base station using the cellular network. If the first method is chosen, we need to design a reasonable forwarding algorithm to route the information from the cluster head to the nearest roadside unit, since the distance from the cluster to its nearest roadside unit is often very long. The advantage of this approach is that the overhead of uploading the information to the traffic management server is almost negligible. For the second approach, vehicles can transmit messages via base stations with little delay, but the disadvantage is the additional cost of transmitting cellular data.

## 2.2 Design of Information Interaction Analysis in ITS Layout

To improve the existing spatiotemporal correlation study design, this section proposes a Kronecker Spatio-temporal compression combining k-means clustering, Kronecker structures, and CS theory. The overall framework of this mechanism is shown in Figure 2.

The purpose of the system designed in this paper is to prompt the traffic management server to respond to traffic events through the timely reporting of events by vehicles. When a vehicle detects an event on the road, such as a traffic jam, vehicle accident, or road damage, the driver or passenger can use pre-installed software to record the event in the form of pictures, text, or video. The vehicle then encapsulates this recording into messages and uploads them to the traffic management server. The traffic management server acts immediately upon receiving the details in the message [25]. Finally, the notification message is broadcast to passing vehicles via the roadside unit. The biggest challenge in implementing this system is to ensure that the traffic management server can respond promptly. Message upload latency and message accuracy are the two major factors that affect system performance. To reduce the impact of these two factors, we propose a group-aware approach to collect information and improve the accuracy of the reported information. To reduce the communication cost, we integrate the cluster-based approach into the information

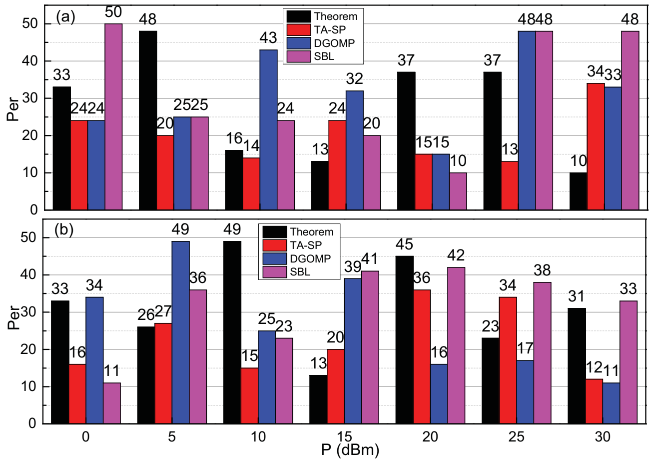

**Figure 3** Successful Detection Rate of the System.

collection process. In each cluster, cluster head nodes collect information perceived by cluster members and extract features from the collected information to compile accurate information about the events that have occurred. To maximize individual utility, the cluster head chooses an upload policy for the generated information, i.e., it can upload via a base station or roadside unit. If uploading via a base station is chosen, then the delay in information transmission is negligible, but the cost of transmission is high. If the road-side unit is selected for uploading, we need to plan a geographic route to propagate the information to the nearest road-side unit, which has the advantage of incurring no additional transmission cost, although it causes some transmission delay. Also, this paper proposes a delay-sensitive routing method for finding the best route from the vehicle to the roadside unit with minimal delay in information transmission.

We verify the previous analysis of the detection success rate and channel estimation error of the GF-NOMA system based on stochastic geometry. The system parameters are: cell inner diameter $r_0$ = 10 m, outer diameter $r_1$ = 150 m, preamble length L = 120, noise power on each subchannel 110 dBm, total number of users J = 240, user activity rate ACT = 0.1, and user transmit power P = 20 dBm, as shown in Figure 3.

Next, we compare the GOMP algorithm with the DGOMP algorithm. The GOMP algorithm performs better when the number of PRBs of the transmission frequency is B = 1 or 2 and the number of active users is less than 10, or when B = 4 and the number of active users is less than 12; as the number of active users increases, the DGOMP algorithm outperforms the GOMP algorithm. This is because when the number of active users is low, the a priori information about user activity enables the GOMP algorithm to make more accurate decisions about active users. However, when the user activity is high, the non-orthogonal nature of the bootstrap produces some false positives; GOMP terminates the iterations as soon as the number of active users detected reaches a present value so that some active users are ignored, while DGOMP continues to iterate as long as the undetected active users are detected in the residuals [26]. It should be noted that both the CoSaMP and GOMP algorithms are based on precisely-known user activity, and this "unpredictable" assumption is unrealistic. In real-world systems, these two algorithms usually assume an empirical value or an average value for the user activity. This has some serious consequences: if the actual number of active users is smaller than the present value, more false detections are introduced, which introduces exponentially more complexity into the JMPA algorithm; if the actual number of active users is larger than the present value, more missed detections are introduced, which seriously affects the reliability of the system.

On the one hand, these small and medium-sized logistics companies have difficulty in expanding their storage facilities and buying distribution equipment in the short term due to financial constraints; on the other hand, they have a large number of e-commerce customers with a large demand for integrated warehouse distribution services, placing pressure on their warehouse distribution resources. At the same time, these companies do not have adequately trained and experienced warehouse personnel, they have less logistics and warehousing equipment, and are lagging behind in terms of adopting and implementing information technology, information processing capability, and data prediction technology, resulting in a low utilization rate of warehousing resources. How to deal with these challenges has become a problem for most of the small and medium-sized warehouses. The key to resolving this problem is to build an integrated management system in which two major subsystems – a warehouse management system and a distribution management system – play vital roles in achieving the organic combination of warehouse.

## 2.3 Application Design

There is a wide variety of methods for inventory demand forecasting, so before starting the inventory demand forecasting work, a scientific and reasonable forecasting method should be chosen according to different forecasting goals and objectives, and the model should be built based on the following principles: the actual prototype of inventory demand is a multi-factor, multi-level, complex variable scenario. Because of the unique characteristics of small and medium-sized integrated warehousing and distribution

**Table 1** Components.

| Constituent elements | Description | Number |
|---|---|---|
| Goods | Type, packaging, quality, volume, etc. | 2 |
| Vehicle | Model, load capacity, vehicle volume, transportation distance, number of vehicles, etc. | 4 |
| Client | Distribution demand, distribution frequency, distribution point, etc. | 2 |
| Optimize the target | Vehicle driving distance, number of vehicles used, delivery time limit, cost, etc. | 4 |
| Restrictions | Meet time window requirements, meet customer distribution needs, meet vehicle load capacity, etc. | 5 |
| Delivery route | Distribution center to customer path, customer to customer path, customer to distribution center path, etc. | 7 |
| Delivery center | Gathering goods, loading and unloading goods, completion of vehicle distribution tasks, etc. | 6 |

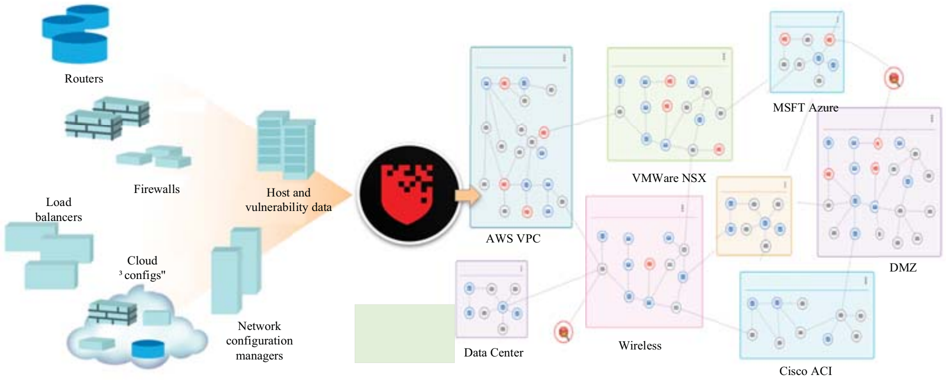

**Figure 4** Network Model.

enterprises, and the influence of complex factors in the e-commerce environment, the selection of models should meet the principle of applicability. The inventory forecast results for demand are used to guide the formulation of inventory plans and replenishment strategies. Although it is difficult to make accurate forecasts due to the influence of the e-commerce environment, it is still necessary to ensure that the forecasts have a small margin for error. The distribution vehicle path problem (VRP) studied in this paper is related to the planning of appropriate distribution vehicle routes as part of coordination and distribution operations.

When an accident occurs or is detected by a vehicle on its route, it can record the event in the form of text, images, or even short videos. In this survey, the respondents wanted virtual simulation teaching content for exercise physiology, exercise technology analysis and diagnosis, and exercise rehabilitation, with the selection rates of 79.21%, 71.25% and 67.89% respectively, while the selection rates of exercise anatomy and exercise biomechanics were slightly lower than the first three at 63.25% and 51.28% respectively [27].

In terms of the contents of virtual simulation experimental education, the respondents strongly prefer receiving information about exercise physiology, exercise technology analysis and diagnosis, and exercise rehabilitation, but they also have a high demand for exercise anatomy and exercise biomechanics. Further analysis also reveals that there is no huge gap in the respondents' demand for virtual simulation experimental teaching content, which indicates that respondents have diverse demands, as shown in Figure 4.

In order to further clarify the correlation between the cognitive elements of experimental teaching, between the cognitive elements of virtual simulation experimental teaching and between the two, the correlation analysis of the questionnaire data of these two dimensions was conducted using the SPSS22.0 statistical software of IBM Corporation.

First, SED is an important metric used to evaluate the clustering effect. It is calculated based on the distance between the cluster head and the cluster sensor node as follows:

$$\mathrm{SED} = \sqrt{(a_i - a_j)^2 - (b_i - b_j)^2 + (c_i - c_j)^2} \tag{6}$$

Second, to evaluate the energy consumption of communication between sensor nodes and cluster head nodes, the communication energy consumption is defined here as:

$$Er = (Erx + EDA) \times Q - (EDx + ERA) \times P \tag{7}$$

Finally, the most important evaluation indicator is RRE, which is recorded as:

$$RRE = \frac{\|X - X^2\|_2^4}{\|X\|_2} \tag{8}$$

RRE for different compression ratios (CR) is defined as:

$$CR = \frac{\left|ML_i^j - nl\right|^2}{NLM} \tag{9}$$

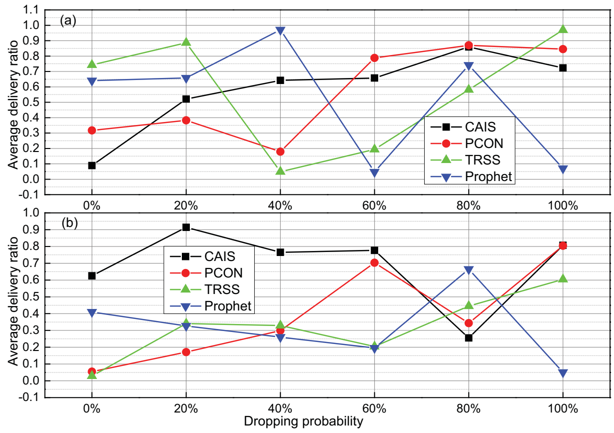

**Figure 5** Average Transmission Efficiency of the Algorithm With Varying Packet Loss Rate.

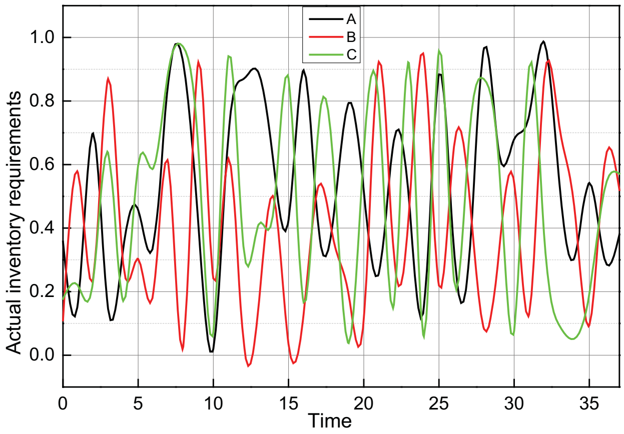

**Figure 6** Original Inventory Demand Series.

Thanks to the rapid development of low-power chips, the power consumption of end nodes has been significantly reduced, greatly extending the lifetime of wireless low-power IoT. Based on the use of many low-power chips, it has been difficult to further reduce the power consumption of nodes, so much of the research on low-power based on terminal nodes has gradually shifted to energy-harvesting techniques and energy-efficient protocols. In this paper, we propose a general energy optimization mechanism based on terminal nodes to reduce the power consumption of sleeping nodes to achieve global energy optimization, mainly for ultra-low duty cycle wireless low-power IoT. Currently, the main optimization target of energy-efficient protocols is the active state of nodes, and there is still a lack of research on energy optimization for the dormant state of end nodes.

# 3. RESULTS ANALYSIS

## 3.1 Cluster Effects Analysis

The basic principle is that before the data transmission starts, the cluster head node checks the routing table maintained by itself, and if there is no next-hop node, it randomly selects the nodes within the communication range and updates the routing table; if there is routing information of the next-hop node, it builds the forwarding path according to the pheromone concentration until it finally reaches the sink node. The ant colony algorithm is a heuristic algorithm that evolved from observations of the foraging habit of ants. The pheromones on each forwarding path will evaporate over time, but the ants will release pheromones again when they pass by, and the pheromone concentration on the node will increase accordingly. Similar results can be seen in Figure 5.

Inventory demand data is a type of time series, and when making time-series predictions, a smoothness check is needed because smooth time series can make better predictions than non-smooth time series. The original inventory demand series is shown in Figure 6.

From the model results, both the LSSVR prediction model and SVR prediction model, the RE and MAD values of CSD hybrid are lower than those of single-support vector regression model; the horizontal error RMSE effect is also better, and the horizontal prediction accuracy is higher; the value of the directional statistic of CSD hybrid model is higher than that of a single model, which proves that the prediction of CSD hybrid algorithm is better than the single model for directional prediction. It also improves the accuracy of the prediction model. By evaluating these four indicators, we can determine the effective of the compression-aware denoising on the prediction model to improve the prediction accuracy. The RE and MAD values of LSSVR are lower than those of the support vector regression model for both the hybrid- and single-prediction models; the horizontal error RMSE is better and

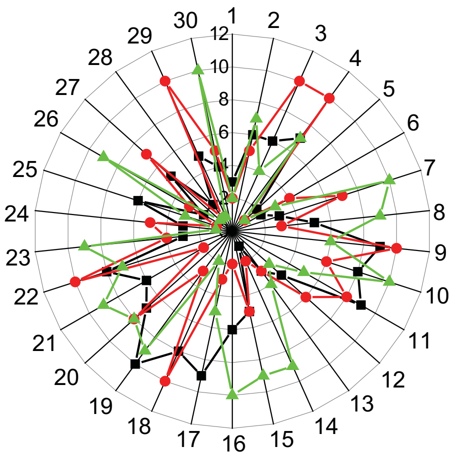

**Figure 7** Energy Consumption Comparison.

the horizontal prediction accuracy is higher; the directional statistics are higher for LSSVR than for SVR, which proves that the LSSVR prediction is more accurate than SVR in terms of directional prediction accuracy. It also has better results. The evaluation of these four indicators has shown that the LSSVR algorithm is superior to the SVR algorithm in the inventory demand prediction model. In combination with the different connotations of intelligent construction management, the intelligent construction information sources are divided into intelligent construction cost information source, intelligent construction schedule information source, intelligent construction quality information source, and intelligent construction safety information source. According to the whole industry chain control perspective in project construction, the intelligent construction information source can be divided into intelligent construction upstream material supply information source, intelligent construction process information source, and intelligent construction product information source.

According to the regional and spatial division of the construction process, the wisdom construction information source can be divided into wisdom construction site information source, wisdom construction off-site information source, or other information sources specifically differentiated by specific partition and spatial distribution. The information sources can be divided into tangible information sources and intangible information sources according to the type of entity involved in intelligent construction. It is also possible to divide the information sources in intelligent construction according to different stages in the construction process of “exploration and measurement – planning and design – construction"; this includes the survey information sources of the exploration and measurement of intelligent construction projects, such as drones, satellites, laser measuring instruments or GIS virtual platforms for terrain and surface image identification, as shown in Figure 7.

Figure 7 depicts the relationship between the average power split ratio of the cluster head for energy harvesting and the maximum allowable transmit power for different SNR conditions. The lower the SNR (e.g., INR = 5dB), the less energy is harvested by the cluster head. This is because the lower the signal-to-noise ratio, a large part of the energy received from the antenna needs to be divided for information processing to ensure that the system’s information communication capacity requirements, the higher the data transmission rate for the network, the higher the energy efficiency of the entire network. In contrast, in Figure 5, the higher the SNR level, the greater the probability that the receiving node or cluster head will allocate more of the received energy for energy harvesting in a region where the interference is limited.

## 3.2 Analysis of Traffic Layout Results

For the simulation of this mechanism, the dataset consists of real environmental data collected by [Intel Berkeley Lab]. A set of humidity and temperature data, both of size 500, where the number of clusters $k = 4$ is an empirical value for the network scenario, is chosen to give a more comprehensive evaluation of the performance of the proposed mechanism.

The performance of the proposed F-KSCD mechanism is compared with two other recent representative schemes: alpine skiing, racing, boarding and other dangerous sports can be done indoors, virtually eliminating avalanches and other accidents, and virtual computer technology creates a virtual scenario that is difficult or even impossible to achieve. Virtual reality technology has an inherent advantage in the familiarization of competition mode and the training of the adaptability of the competition field. Based on the huge amount of competition information and athlete competition records stored and collected by the Internet, it is possible to model specific target competition information as a trainer for daily training, making the training more targeted. For some sports that are restricted by national, regional, religious, cultural, and other factors that prevent them from training at a higher level, computer virtualization technology can help to overcome this limitation, as shown in Figure 8.

We can see from the above analysis that the virtual simulation experimental system of “assessment of human movement ability and fitness path design” has achieved a good degree of satisfaction and acceptance; from the feedback of the four evaluation angles of interactivity, ease of use, usefulness and motivation, we conclude that the system can

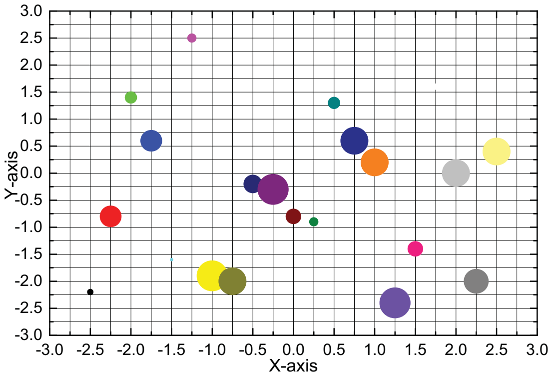

**Figure 8** Distribution of Industrial Nodes After Clustering.

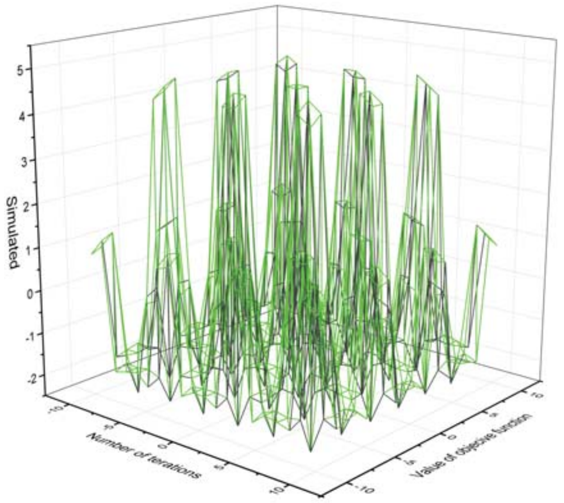

**Figure 9** Convergence Properties of Intercorrelation.

build a virtual simulation experimental teaching scenario with good interactivity, so that the test subjects can use the virtual experimental equipment and instruments easily, freely and fluently to learn and explore sports knowledge independently, and improve their sports knowledge, practical application ability and learning motivation, as shown in Figure 9.

As the CR increases, the RREs of each scheme gradually increase. The rules for the optimization scheme are 0.038 and 0.012, respectively, while the RREs for the other two schemes are 0.1246 and 0.1244, respectively. Thus, among these schemes, F-OKSCD has the lowest RRE, which is much smaller than F-KSCD, indicating that the optimized design of the fog node Kronecker joint observing matrix is a good example of the optimization of the fog node Kronecker joint observing matrix. Also, from these results, it can be concluded that for humidity and temperature data, F-OKSCD improves the RRE of the current mechanism by an average of 16.8% and 18.9%, respectively.

Figure 10 shows the transformation coefficients of the original data under the DCT dictionary base. From the sparsity analysis, the sparsity of the temperature data is still very low after DCT thinning, and there are still many non-zero elements in 500 data. This sparsity is not sufficient to achieve a high reconstruction accuracy for the CS reconstruction conditions. In this mechanism, two 40×500 spatial and temporal databases are created which are used to train the spatial and temporal dictionaries, respectively. Figure 10 shows the transformation coefficients of the raw data based on the training dictionary. The 500 data are quite sparse, with only 16 non-zero elements in this transformation base. This shows that the mechanism's dictionary training method is very effective and that the original data can be easily reconstructed with very high accuracy after compression.

Combining the two simulations in Figure 9 and Figure 10, we can conclude that although the DCT base can be very sparse for the data under ideal conditions, the sparse effect of the DCT base is negligible in the realistic complex IoT environment. The dictionary training method designed by the mechanism, when applied to an IoT scenario, achieves an excellent sparse effect, which has a great impact on the compression performance of the whole mechanism. This is a comparison of the compression reconstruction error before and after the mechanism weighs the sparse bases and observation matrices (joint optimization). It can be seen from this figure that the reconstruction error after the trade-off (i.e., after the joint optimization of the sparse bases and observation matrices) is always smaller than the error before the trade-off regardless of the value of the compression ratio. On the one hand, it proves that training the sparse bases and optimizing the observation matrix alone cannot make the reconstruction error

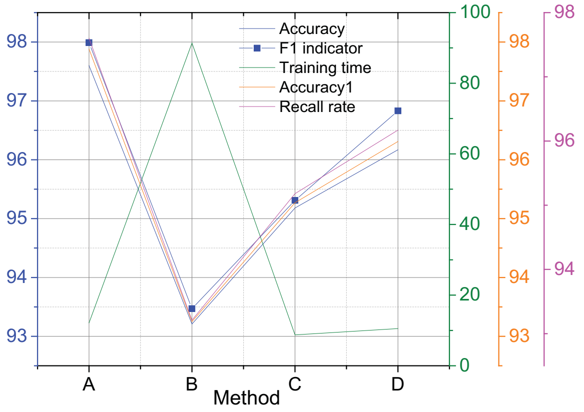

**Figure 10** Sparsity Results.

of the compression scheme reach the theoretical minimum; on the other hand, it also shows that there is a correlation between the sparse bases and the observation matrix, which can be weighed well by some joint optimization, thus reducing the error in the data reconstruction.

## 4. CONCLUSION

In this paper, we extend the study on the performance improvement of Kronecker space-time compression based on k-means, by optimizing the observation matrix based on Kronecker space-time compression and flexibly applying it to IoT scenarios, so that this mechanism not only ensures the successful execution of CS data reconstruction, but also the data pre-processing of fog nodes. Also, based on the Kronecker joint observation matrix optimization model, an optimal solution method for Kronecker spatiotemporal joint observation matrix is designed, which can minimize the correlation between the observation matrix and sparse bases and reduce the autocorrelation of the observation matrix. Correlation enables the matrix to be adapted to various real-life scenarios to further improve the quality of reconstructed data. The high-power consumption of mid-side units in Telematics can lead to data transmission delays and even interruptions. On one hand, existing studies only consider roadside devices as the only energy-consuming devices in the network without considering other energy-consuming endpoints, such as electric vehicles and sensors; on the other hand, only the downlink energy consumption of roadside units is considered in terms of energy saving. The simulation results show that the algorithm can make the roadside unit obtain enough energy and provide continuous service for the passing vehicles. Secondly, an energy-saving, task-scheduling mechanism based on fog computing is proposed, which optimizes the overall energy consumption of the roadside unit and achieves a balance between delay and energy. The simulation results show that the algorithm can enable the roadside unit to obtain sufficient energy and provide continuous service to passing vehicles. The simulation results show that the algorithm can reduce energy consumption while ensuring the task completion delay.

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