Hindawi
Journal of Sensors
Volume 2024, Article ID 9767923, 1 page
https://doi.org/10.1155/2024/9767923

Retraction

Retracted: Research on Interactive Design Algorithm of Folk Museum Exhibit Map Based on Intelligent Wireless Sensor Network

Journal of Sensors

Received 23 January 2024; Accepted 23 January 2024; Published 24 January 2024

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Li, "Research on Interactive Design Algorithm of Folk Museum Exhibit Map Based on Intelligent Wireless Sensor Network," *Journal of Sensors*, vol. 2023, Article ID 5239929, 11 pages, 2023.

Hindawi
Journal of Sensors
Volume 2023, Article ID 5239929, 11 pages
https://doi.org/10.1155/2023/5239929

Research Article

Research on Interactive Design Algorithm of Folk Museum Exhibit Map Based on Intelligent Wireless Sensor Network

Yifei Li

Guangzhou HuaShang College, Faculty of Applied and Creative Arts, Guangzhou, Guangdong 511300, China

Correspondence should be addressed to Yifei Li; yikfeilee@gdhsc.edu.cn

Received 10 August 2022; Revised 7 September 2022; Accepted 5 October 2022; Published 24 March 2023

Academic Editor: Gengxin Sun

With the continuous improvement of people's living standards, people's pursuit of material life and satisfaction of spirituality are also increasing, and the demand for culture and value orientation are also diversifying. As an important position of many cultural consumption places, museums have seen an unprecedented increase in their cultural radiation and public attention. In such a large social environment, the nature museum industry increasingly recognizes that to make full use of the role of museums and better reflects the characteristics of the industry, it is necessary to introduce visual image design into museums. However, visual imagery design in domestic museums is still in its infancy; only a few large national museums have adopted visual imagery design, while relevant research in small folk art museums is still rare. This paper takes Guangzhou Folk Museum as the research object, based on which a new model of interactive design of Guangzhou Folk Museum display map using intelligent wireless sensor technology is proposed, combining the industrial characteristics of folk art and the visual imagery characteristics of Guangzhou Folk Museum. By analyzing the performance of the core algorithm of this system, it is concluded that the performance of the system is very good. However, the application of this model can enable the Guangzhou Folk Museum to establish the brand image of Guangzhou Folk Museum and create more folk culture value in the face of new opportunities and challenges.

1. Introduction

Museums are the result of socialization, and they are the repositories of knowledge that document the history and cultural development of human beings. With the rapid socioeconomic development, the number of museums is rapidly growing, their classification is clear and their quality is generally improving [1]. As an important platform for the exchange of human civilization, in recent years, many cities, large and small, can be seen everywhere in the process of new or reconstructed museums, or through the visual image design of the logo, the layout of the pavilion, and the surrounding cultural derivative products, to brand the museum and attract more tourists to visit, in order to promote the sustainable development of the museum in the market competition and give full play to its propaganda role.

Compared with ordinary comprehensive museums, folklore museums have regional characteristics and have a strong thematic focus. The birth of folklore museums is with the continuous improvement of people's living standards, the diversification of cultural industries, and the inheritance and protection of national culture, and the emergence of folklore museums makes China's museum system more complete [2]. Folklore museums are the main places for folklore collection, folklore crafts, folklore culture dissemination, and communication, gradually moving away from comprehensive museums and gradually developing with their own unique perspective.

As more and more people enter folklore museums, their social and educational roles are increasingly strengthened, and new folklore museums are emerging, which inevitably involve folklore museums in the competition of the market, and how this small group of folklore museums can survive in the increasingly fierce competition becomes a very important issue [3–5]. In such a social environment, the traditional "good wine is not afraid of the alley" business model has shown more and more limitations in the fierce competition of other cultural industries.

A good brand image is essential for an ethnic museum, and a good brand image is the only way to win the market competition. In recent years, the hardware construction of folk art museums has made certain achievements, such as expanding the scale of the exhibition hall, introducing multimedia technology, and enriching exhibits, but the relevant image design and other aspects have not received sufficient attention. In terms of visual image design, China's folk art museums lack systematic design and promotion, and do not integrate them with the operation concept of enterprises. Compared with excellent folk art museums abroad, domestic products present a rough and scattered form and cannot form an overall advantage.

Therefore, this thesis conducts an algorithm study on the interactive design of folklore museum exhibition map with the background of intelligent wireless sensing network. Its purpose is to use the power of the network to create a more technological folklore museum brand, which is conducive to highlighting the personality of the regional folklore museum, better attracting the attention of the public, allowing more people to understand the regional folklore culture, better inheriting and developing the regional folklore culture at the same time In addition, it will enhance the visibility of regional folklore museums in the industry.

2. Introduction to Related Theories

2.1. Overview of Folk Museums. Folklore museums are an important part of museums in China, but there is no clear definition abroad, and they are often classified as "folklore museums"; that is, "ethnic folklore". Folk museums coexist with folklore [6] and have the functions of collection, conservation, education, dissemination, and research but also have their own distinctive characteristics, and the difference with general museums lies in folklore, protecting folk crafts, residential life collections, and folk customs, and taking on the important responsibility of passing on folk lifestyle and traditional culture. In his book "Introduction to Chinese Ethnic Folk Museums", Antinshan defines "folk museum" as "a museum of folklore, a place of local customs and living culture, which exists to let people understand the local customs and functions and characteristics, so as to inspire people's love for their hometown and homeland."

The exhibits of the folklore museum are mostly from the sources of cultural relic's collection, donations from folklore collectors, etc. The display method is based on restoring folklore life scenes and real objects displaying and setting up, and the use of lighting effects, plaster model shaping, and picture display enriches the exhibition form of the folklore museum [7–9]. At the same time, with the development of society and the strong support and protection of folk crafts by the state, folk museums have a new function: experience function, thanks to the support of modern multimedia technology and the display of crafts held by folk museums, making the popularization of folk culture, from the original intuitive visit mode to the visitors' hands-on experience, which improves the fun of the public when browsing folk museums.

2.2. Composition of Wireless Sensor Network. A wireless sensor network typically consists of a large number of microsensor nodes randomly distributed within or adjacent to the monitoring area, and forms the network in a self-organizing manner. The data collection and transmission in sensor networks are generally in multihop mode.

The sensor network generally consists of three parts, i.e., sensor nodes, aggregation nodes, and task management nodes, as shown in Figure 1. Sensor nodes are responsible for collecting and gathering monitoring data [10], and transmitting the monitoring data to aggregation nodes in a path, then performing the necessary fusion, and then transmitting them to task management nodes via the Internet or satellite communication. The task management nodes in the system are mainly responsible for configuring and managing the sensor network, issuing monitoring tasks, and collecting monitoring data.

The sensor node has communication, sensing, and computing functions, and it includes a wireless communication module, a processor module, a sensor module, and a power module. The communication, processing, and storage capabilities of the network are generally low. Sensor nodes have various functions such as acquisition, processing, management, fusion, and storage, and work in collaboration with other nodes.

The aggregation node has strong communication, computing, information processing, storage capabilities, and connects it to the external network and delivers the collected information to the external network. The aggregation node can also switch between two different protocol stacks of WSN and the Internet, and release its monitoring tasks to the WSN network [11].

Wireless communication module is mainly responsible for wireless communication with other nodes to achieve the exchange of information, reception, etc. The main function of the sensor module is to complete the collection and transmission of information within the museum space; the processor module mainly completes the control of the functions of the entire node, and the data collected for storage, processing; energy supply module to provide energy for the entire node, generally using small batteries. The sensor node composition is shown in Figure 2.

2.3. The Intrinsic Connection between Interaction Design and Folklore Museum Display Design. Interactive design is a way of museum display purpose, it is the most peripheral one, and its goal is to create a display space with interactivity, which is its internal function. In other words, interactive design should be based on display function, and the development of interactive design form will also have some influence on the realization of display function; no matter the influence on the form or the function, their ultimate purpose is to achieve the purpose of museum display [12], which is to effectively convey information. This paper summarizes the intrinsic relationship between interactive design and museum display design: (1) interactive display space is the goal of interactive design, that is, function; (2) interactive design is a way to achieve interactive museum display and plays a counter role in interactive display; and (3) the two have a discursive, unified relationship, and the meaning of

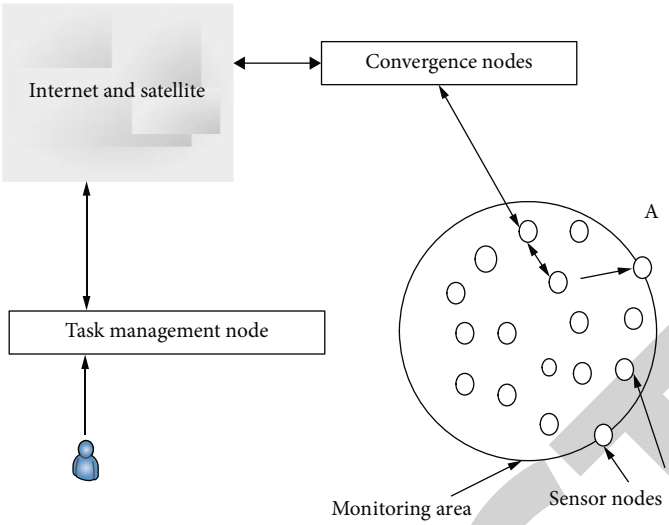

Figure 1: Wireless sensor network composition (Internet deep learning public dataset).

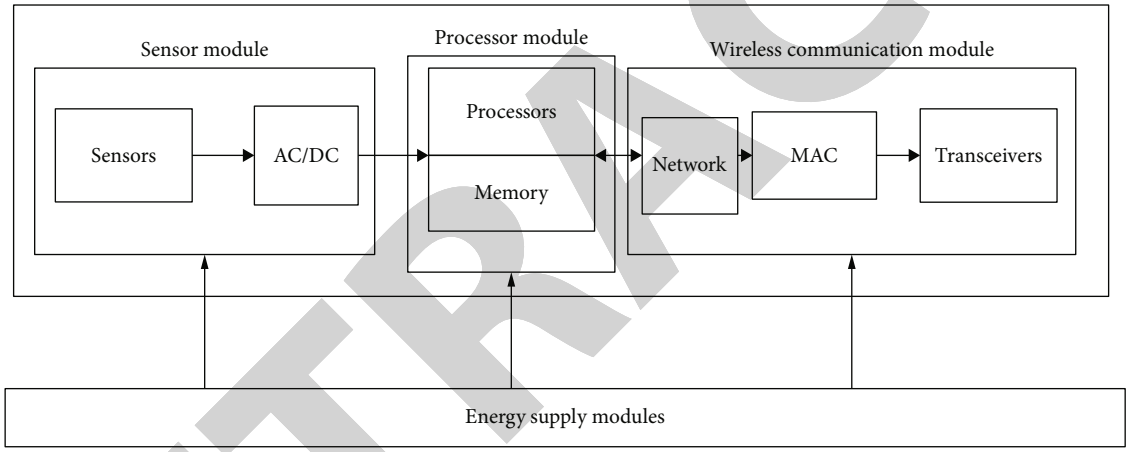

Figure 2: Sensor node composition.

their existence is to achieve the basic information transfer of museum display activities.

3. Application Method Design

3.1. Folk Museum Display Design Principles. The folklore museum is a building with distinctive industrial nature, which is based on folklore legends and spreads local folklore culture to the public; therefore, when designing the visual image of the building, certain design principles must be followed to enable the design work to be carried out smoothly. This paper summarizes four basic design guidelines from the principles of VI design, combined with the industrial characteristics of folklore museums.

3.1.1. Folklore Theme. Before the visual imagery design, the theme, which is a flag, must be clearly understood so that it has a clear connotation, thus making the designed visual imagery more recognizable [13]. The recognizability contains two levels: one is the difference between industries, and the other is the subdivision within the industry. It is necessary to have a deep understanding of the characteristics of the products so that the visual imagery design not only has clear industry characteristics but also can be unique in the same industry.

3.1.2. Locality. The visual imagery of the folk museum is the external image of the museum, which is the external embodiment of its business philosophy and folklore culture. China's folk style has obvious regional characteristics, and the folk tradition of different winds in ten miles and different customs in a hundred miles makes the visual image of the museum to take the regional culture of the museum as the background, plus the local visual elements to accurately convey the folklore story, so that each museum has its own characteristics in visual. When adhering to regional characteristics, two points should be noted as follows: first, the reference of visual imagery has regional characteristics and the subtle influence of regional culture on designers; on the other hand, the visual symbols distilled should be compatible with local customs and habits and have greater emotional resonance with local people.

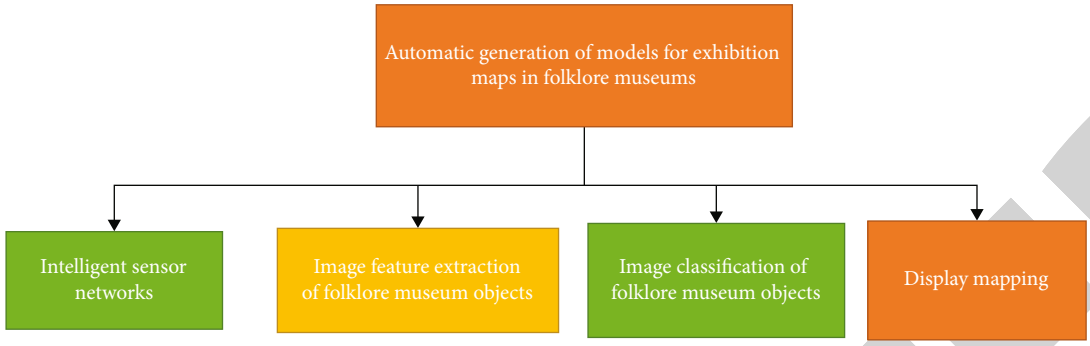

Figure 3: Architecture of automatic generation of exhibit map of folklore museum.

3.1.3. Aesthetics. Beauty can produce feelings, and in the visual imagery design of the folk museum, to appreciate beauty, it is necessary to resolve the contradiction and integration between the elegant and vulgar cultures in folklore and folklore. The folk museum exhibits some folk culture products, most of which are labeled as "vulgar" ("vulgar" means "popular" and "simple and easy to understand"). The word "vulgar" refers to "popular" and "simple and easy to understand", and even has a "vulgar" component, because folklore is rooted in the people, compared to the mainstream culture, folklore is more focused on the art of folklore, so when appreciating, often pay too much attention to the "vulgar", the subject matter and presentation Therefore, when appreciating folklore, we tend to pay too much attention to "vulgarity", and the subject matter and expression are based on the theme of rural living environment.

3.1.4. Systematic. Shaping the visual imagery design of folk museum is to make its visual imagery and its thematic meaning have logical consistency [14]; that is, the development of its visual elements is an internally coherent whole, which can be conveyed to the audience in accordance with the main and sequential order.

3.2. Automatic Generation Model of Folk Museum Exhibition Map. Since the traditional supervised deep learning algorithm cannot solve this problem well. The purpose of this thesis is to design an unsupervised deep learning algorithm that can generate the graphics of the map according to the display rules without using the actual values. The automatic generation model of this exhibition map mainly includes this following four modules: intelligent sensor network, folklore physical image feature extraction, folklore physical image classification, and display map drawing. The architecture is shown in Figure 3.

3.3. Folk Museum Object Image Feature Extraction Algorithm. In this paper, the folk museum object image feature extraction is a SIFT-based feature extraction method, which is a local feature detection method used in image processing [15]. This method can identify the feature points of the image and describe them as feature points. The feature descriptor is not only invariant and rotation invariant but also can adapt well to the lighting changes of the image and the changes of the camera angle. The algorithm consists of four main aspects.

(a) Spatial limit of the detection scale. Image retrieval is performed at each scale and a differential Gaussian method is used to find feature points that may be insensitive to angle and scale

(b) Localization of feature points. At each candidate location, the specific location and scale of each candidate feature point are determined based on its stability, respectively

(c) Determination of the orientation of the feature points. For each feature point, one or more directions are determined separately based on the gradient direction of the local image

(d) All subsequent processing is performed to transform the orientation, scale and position of each feature point to enhance the stability of the features with respect to orientation, scale and position

(e) Generate a feature description. The local gradient of the image near each feature point in the chosen scale space is converted into an expression that adapts well to the deformation and illumination changes of the image

The following is a brief description of each of the several main steps.

(1) Constructing the scale space

This step is performed to simulate the multiple scales of a realistic image. The Gaussian scale space of a two-dimensional image is defined as follows.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y). \tag{1}$$

Among them,

$$\mathrm{G}(\mathrm{x}, \mathrm{y}, \sigma) = \frac{1}{2\pi\sigma^2} \mathrm{e}^{-\left(\mathrm{x}^2-\mathrm{y}^2\right)/2\sigma^2}, \tag{2}$$

is the variable Gaussian function, $I(x, y)$ is the input two-dimensional image, the operator $*$ denotes the convolution

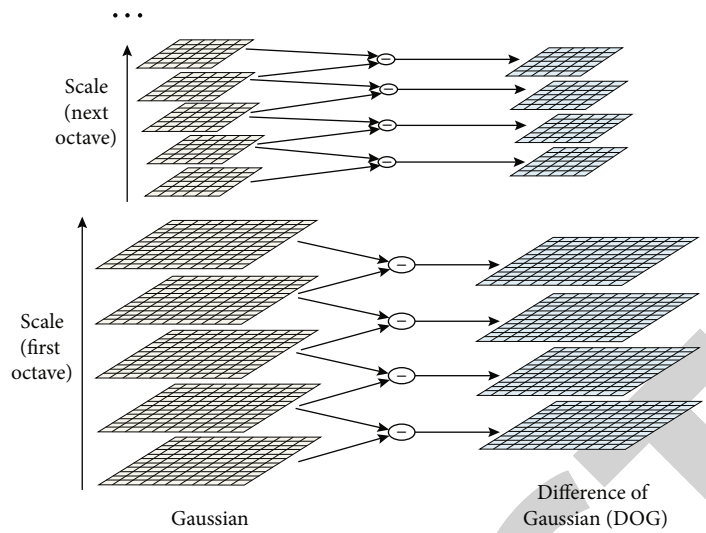

Figure 4: Image pyramid (Internet deep learning public dataset).

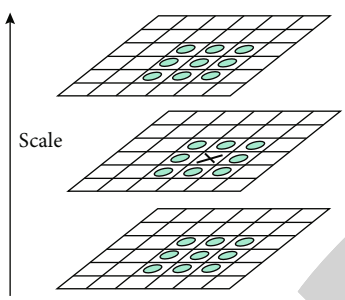

Figure 5: Extreme value point detection (Internet deep learning public dataset).

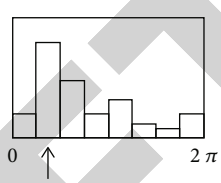

Figure 6: Histogram of feature point directions (Internet deep learning public dataset).

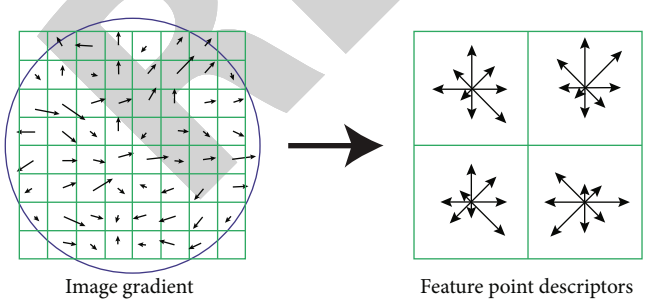

Figure 7: Schematic diagram of the generation of feature point descriptors (Internet deep learning public dataset).

of the spatial coordinates x, y, and σ is the spatial scale factor, which is a standard deviation of the Gaussian normal distribution, i.e., it reflects the blurring degree of an image. In order to extract stable feature points efficiently in the scalar space, Loy proposed a method to convolve the image using a differential Gaussian function as follows.

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma)) * I(x, y) \\ &= L(x, y, k\sigma) - L(x, y, \sigma), \end{aligned} \tag{3}$$

where $L(x, y, \sigma)$ is the Gaussian scale space and k is the scale factor of two adjacent Gaussian scale spaces.

From the above equation, it can be seen that the image of the difference Gaussian function can be obtained by subtracting two adjacent images in the Gaussian space [16]. Therefore, to obtain the DoG image, a Gaussian scale space should be established first, and the Gaussian scale method is to use the image pyramid descent sampling method and then add the Gaussian filtering method, i.e., the image is Gaussian blurred by using different covariance sigs, so that each pyramid has multiple Gaussian blurred images. The schematic diagram is shown in Figure 4.

As can be seen from the above description, the Gaussian pyramid is composed of multiple sets, each of which is of multiple levels. The Gaussian parameters are different for each stratifications and there is a ratio factor k between two adjacent strata of the same set, if each group has a stratum S. If each group has S levels, then $k = 2^{1/s}$.

(2) Detection of feature points in DoG space

In the scalar space, each sampled point is compared with its nearby points to find the extreme value (feature point) in the scalar space [17]. As an example, in Figure 5, the center point is a target detection point. In order to check that this point is a polar point in both scalar space and 2D image space, then eight neighboring points in the same scalar (that is, in the same plane), in the vertical and perpendicular directions (that is, in both planes), are $9 \times 2 = 18$ points. If said target detection points are more than all the points (26 in the example) in this layer of said scalar space and in

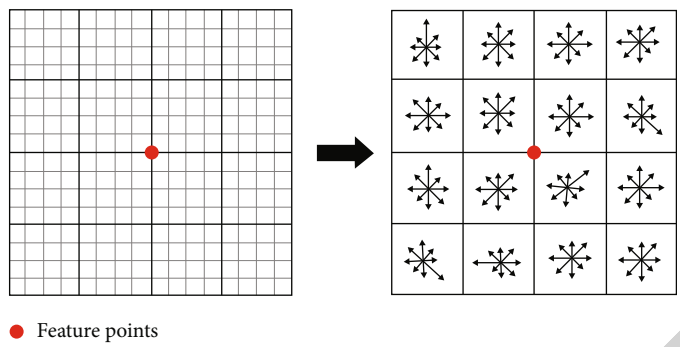

Figure 8: 128-dimensional SIFT feature descriptor (Internet deep learning public dataset).

said upper and lower adjacent regions, then said points can be used as feature points of said image.

(3) Determine the main direction of feature points

With the previous step, we found feature points with different scale characteristics. In this case, it is necessary to orient the feature points to ensure that stable feature points can still be found during the rotation. Here, the orientation covariance of the feature points is determined by the gradient distribution characteristics of the pixel in its neighborhood. After Gaussian smoothing, the scale at which the feature point is located is used to select L. That is, we can know the size of a feature point and thus derive the size of this feature point.

$$L(x, y) = G(x, y, \sigma) * I(x, y). \tag{4}$$

For each image sample $L(x, y)$, the gradient magnitude $m(x, y)$ and direction $\theta(x, y)$ at that scale can be calculated using the following equation.

$$\begin{aligned} \mathrm{m(x, y)} &= \sqrt{\mathrm{L(x+1, y) - L((x-1, y))}^2 + \mathrm{(L(x+1, y) - L(x, y-1))}^2}, \\ \theta(x, y) &= \tan^{-1}((L(x, y+1) - L(x, y\_1))/(L(x+1, y) - L(x-1, y))). \end{aligned} \tag{5}$$

Using the above formula, the gradient values and directions of the adjacent regions are derived using the feature points as the core. Based on this, the histogram of the image is used to count the gradient direction and magnitude of each pixel in the adjacent region. The horizontal coordinate of this histogram is the angle of the slope direction, and the vertical coordinate is the accumulated value of the magnitude in the direction of that slope, and the major direction of that feature point is the slope of that peak in that histogram, as shown in Figure 6.

At this point, the major direction of the feature point is determined, and each feature point has three pieces of information: location, scale where it is located, and direction.

(4) Generating descriptors of feature points

Based on this, we obtain information about the position, scale and orientation of the SIFT feature points. First, the feature vector is rotated invariably by rotating the coordinate axes as the main direction of the feature points centered on the feature points. As can be seen in Figure 7, after rotation, an 8×8 viewport is selected with the feature point as the center, and each small cell represents a pixel in the region near the feature point, while in the center of the left panel is the current position of the feature point. Based on this, a Gaussian window (the circular window on the left side of the figure) is used to calculate the weights of each pixel, where pixels farther away from the feature point are assigned lower weights and pixels close to the feature point have greater weights, and the direction of the arrow in the attached figure represents the gradient of the pixel, while the length of the arrow represents the gradient magnitude [18]. Finally, gradient histograms were obtained for each of the eight directions in a small area of 4×4. The accumulated values in each gradient direction were calculated as a seed point, as shown in the right side of Figure 7, where each feature point contains 4 seed points and each seed point contains information of 8 directions.

The method has good noise immunity. In practice, each feature point is composed of 16 seed points of 4×4, which can thus be represented by a vector of 128 ($4 \times 4 \times 8$). This is shown in Figure 8.

From the above, it can be seen that under the SIFT method, an image will be extracted with multiple feature points, each of which is a feature point of 128 dimensions.

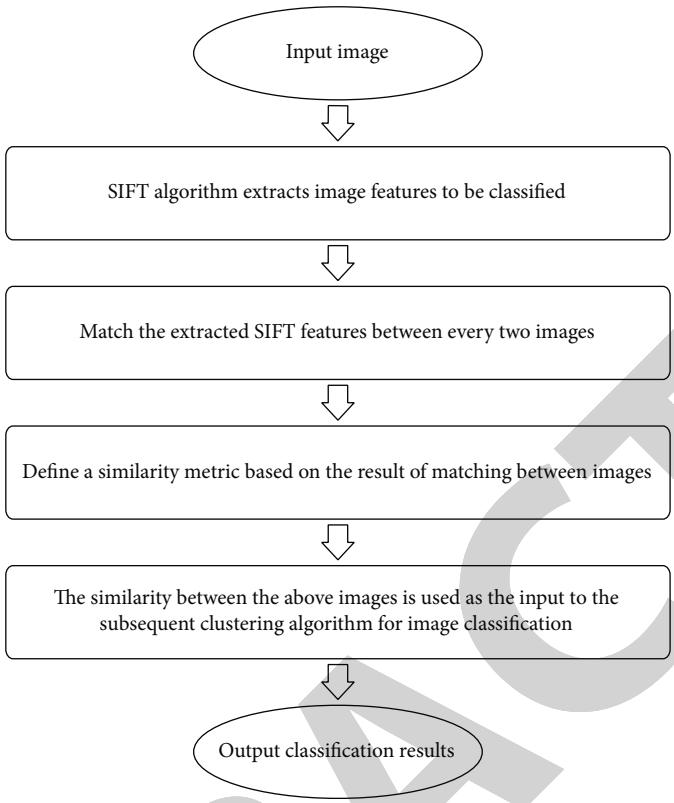

Figure 9: Flow chart of unsupervised image classification based on SIFT (Internet deep learning public dataset)

This SIFT feature can be kept constant in terms of image rotation, image scale, brightness change, etc., and is stable against disturbances such as noise.

3.4. Image Classification of Objects in Folk Museums. At present, the most common method for object image classification in folklore museums is supervised image classification using deep learning model, although its classification effect is better than the previous traditional methods, but it still has some reference value [19]. Therefore, unsupervised classification methods based on clustering algorithms are still of high research value.

Firstly, the feature extraction algorithm is used to match the features of two images, and on this basis, the index of similarity between images is determined and used for clustering to achieve the final classification effect. Therefore, based on the SIFT feature extraction algorithm described in the previous section, the following unsupervised image classification method based on the SIFT feature extraction algorithm is given, and its flowchart is shown in Figure 9.

3.5. Smart Sensor Network Architecture. The main function of the intelligent sensor network is data transfer and processing. The system includes the following: image acquisition module, DSP image processing module, ZigBee network transmission module, ARM central controller, and GPRS remote transmission module [20].

ZigBee technology can build a network structure with star, tree, and grid type. The system uses a ZigBee star network with the following topology: ZigBee Controller and ZigBee End-point. A sensing network consisting of wireless links is established between the coordinator node and the end nodes.

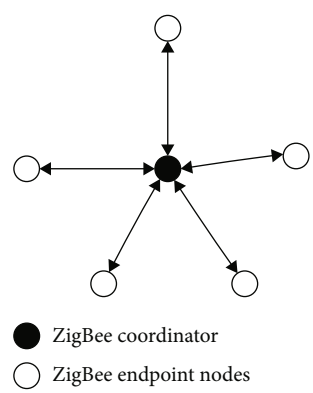

Figure 10: ZigBee star network topology diagram.

Table 1: Accuracy comparison on MNIST dataset.

	Accuracy
SIFT+clustering	99.87%
Random Forest	96.70%
DNN(LeNet-5)	99.04%

All ZigBee end nodes act as image information collectors and are integrated into the ZigBee coordinator program for centralized processing, as shown in Figure 10, the system uses CMOS image sensors to compress and encode the

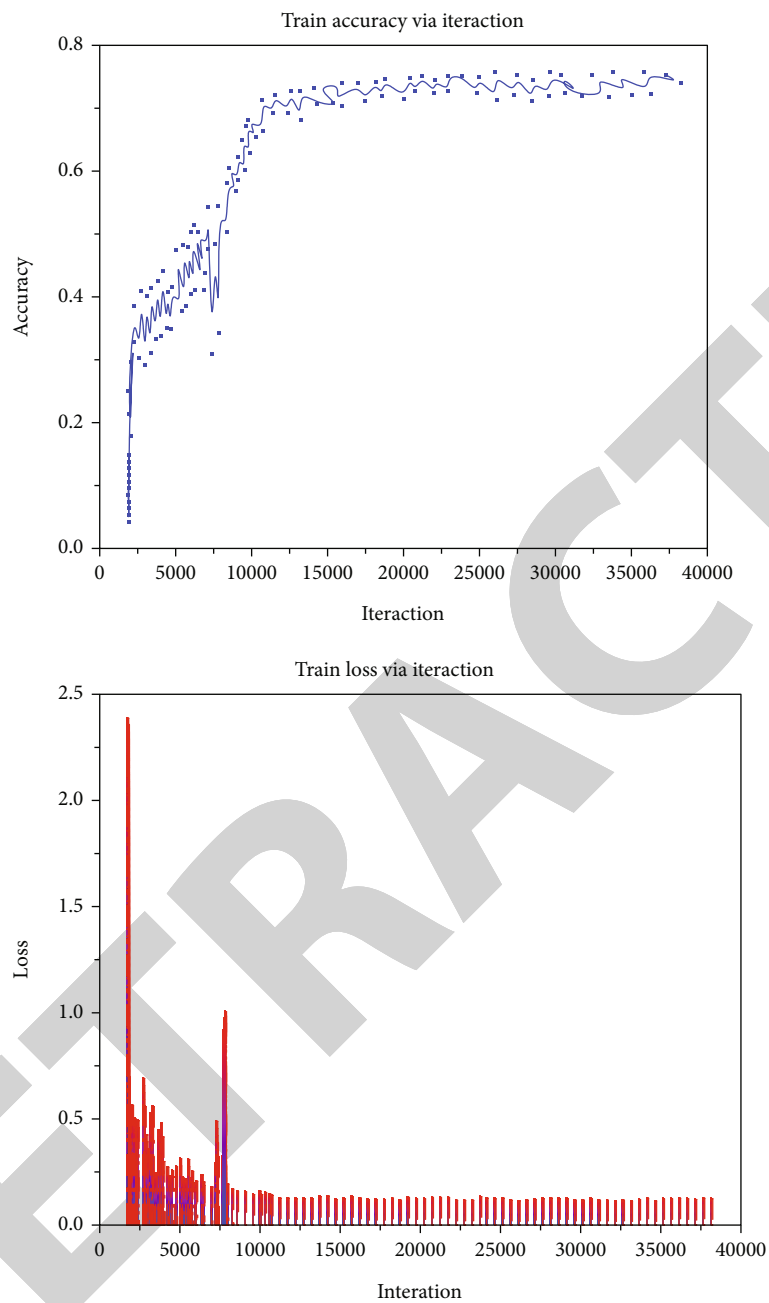

Figure 11: Changes in global correctness and loss values on the training set during 40,000 iterations of the 90,000 pretraining-based model.

images in the pavilion space through DSP, and then realize remote data processing through the ZigBee network and GPRS network.

The specific roles of each component of this system are as follows.

(1) The central control module of ARM. Real-time data acquisition and processing through ZigBee and GPRS networks, as well as data transmission to GPRS and ZigBee

(2) Image acquisition component. Responsible for acquiring simulated images in the spatial scope of the folk museum and converting them into binary image information by using AD conversion technology

(3) DSP image processing module. JPEG compression technology is used to compress and encode the image, reducing the amount of information on the image and making it more suitable for low-rate transmission in ZigBee networks

(4) A ZigBee network transmission component. Transmitting processed image data to a coordinator for centralized processing via a ZigBee network

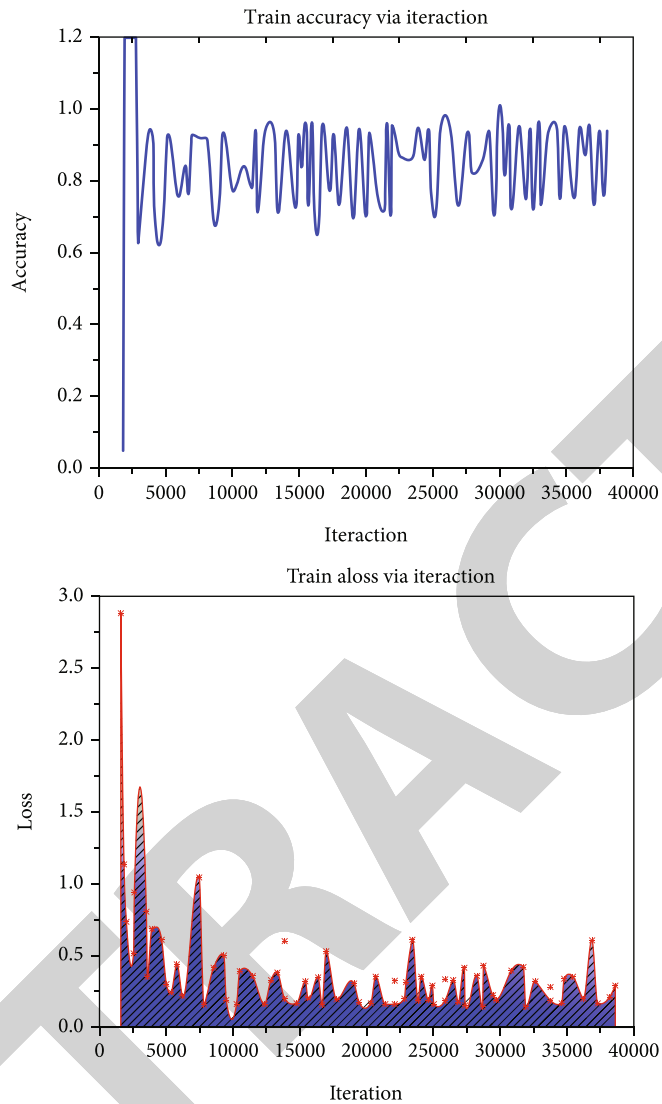

Figure 12: Changes in global correctness and loss values on the training set based on 100,000 iterations of the pretrained model over 40,000 iterations.

(5) A GPRS telemetry device. A GPRS module is used to dial-up the Internet, connect the ARM to the Internet, and set up a UDP server in the monitoring center to which the image data from the UDP client (ARM) is transmitted

On this basis, the three networks of ZigBee, GPRS, and the Internet are used to work together to transmit the image data to the remote data processing center, i.e., the exhibit map generation model performs automatic map generation based on the data.

4. Application Experimental Analysis

4.1. Data Sources and Preprocessing. All data are automatically generated by Python's captcha library, which means there is no limit to the training data. Python's captcha library is a tool that can generate images, and after obtaining the relevant training information [21], only some simple preprocessing is needed to facilitate future operations. The preprocessing consists of two main steps, resizing the image to $68 * 116$ and normalizing the RGB values. After the data preprocessing, the relevant classifications and categorizations are archived in HDF5 as a reference for the data iterator.

4.2. Model Performance Comparison Experiments. The dataset used for the model performance analysis here was automatically generated by Python's captcha library, which includes 60,000 of 28×28 training images and 10,000 trial images. This comparison uses a LeNet-5 model and a random random forest with training techniques such as dropout, and compares this model to the activation function of ReLU. The random forest, on the other hand, has more than two thousand trees. The specific experimental results are shown in Table 1.

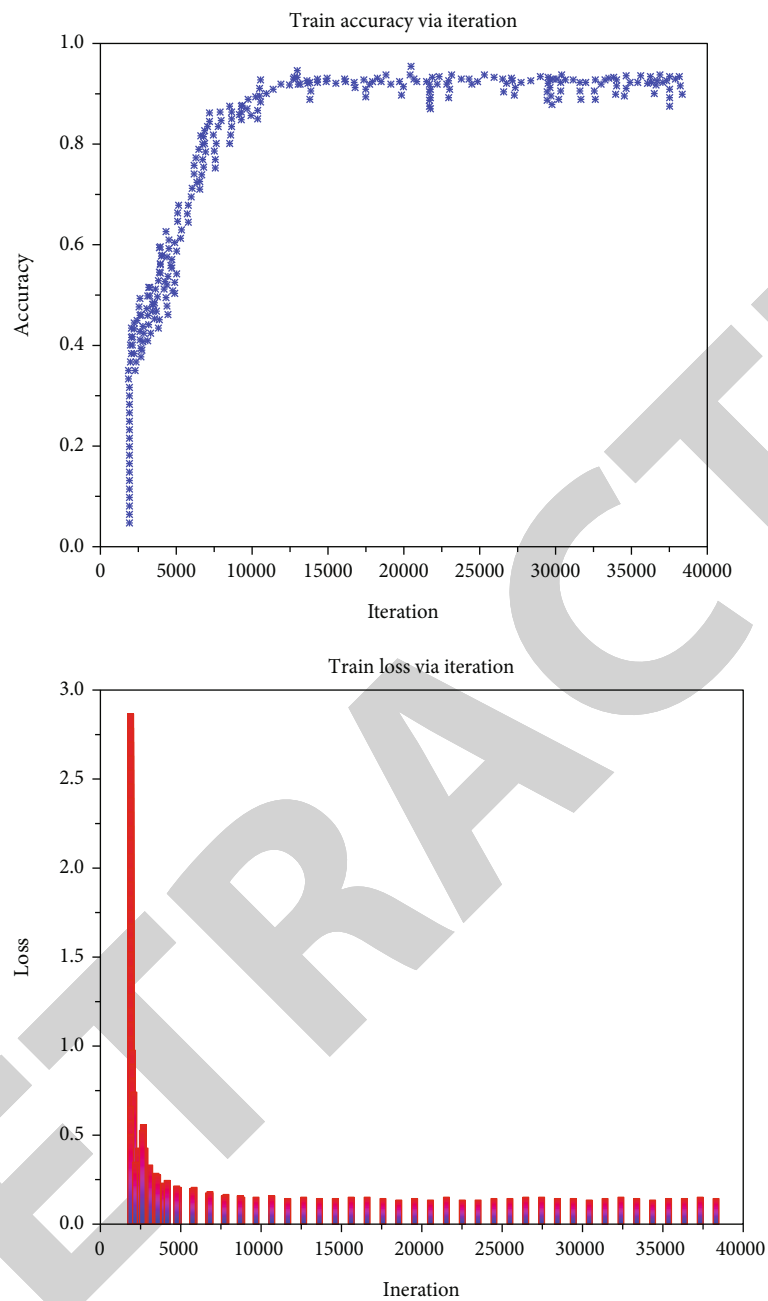

Figure 13: Variation of global correctness and loss values on the training set based on 80,000 pretraining iterations of the model over 40,000 iterations.

From the Table 1, it can be seen that the accuracy of this model can exceed the results of the optimized DNN with the default configuration without tuning parameters, so the results of this image classification can be obtained as very good.

4.3. Experiments on Practical Application of the Model. The performance comparison tests with the model provided in this study allow for practical experimental analysis. And Figures 11 and 12 show the changes in the global correctness and attrition values obtained at 40,000 repetitions of training, based on 90,000 and 100,000 repetitions. Based on our experience, we can see that a pretrained model based on 90,000 repetitions will have a runout in about 7,000 repetitions, but eventually it is pulled back, as guaranteed by our standardized operation. Whereas the model based on 100,000 pretrained results has a loss value that is very unstable when trained, I think this is because the learning rate is set too high, causing the vibration of the motion. Also, the quality of the set of information we labeled was not high and noisy. However, overall, the model also handles the real dataset very well. The changes in global correctness and loss values on the training set based on 80,000 pretrained model 40,000 iterations are shown in Figure 13.

5. Conclusion

At present, the visual imagery design of China's folk museums is still in the primary stage and lacks visual imagery design. At present, only a few folk museums have carried out logo design, mainly focusing on display design, architectural design, and other aspects, while less attention is paid to visual imagery design. The existence of visual imagery will not affect its display and educational functions, but can enhance its external publicity and shape its personal image, while the long-term lack of visual imagery will also hinder its development.

This thesis takes this phenomenon as an opportunity to carry out research and proposes an application model for automatically generating display maps based on museum space and folklore images, which can also be used to explore the attribute characteristics of folklore museums through the folklore image feature extraction method, and the generated display maps can also be used as the principles of visual image design and implementation methods for folklore museums, which will also greatly promote folklore culture It will also greatly facilitate the dissemination and development of folk culture.

Given the resource and time constraints of folk museums and the richness of their connotations, this study still leaves much to be desired, but it is expected to draw the attention of more designers to make their own contribution to the development of museums in China.

Data Availability

The dataset used in this paper are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

Acknowledgments

This work was sponsored in part by the Young Innovative Talents Project of Guangdong Provincial Education Department. Project Title: Research on Exhibition Design of Guangzhou Region Folk Museum Based on Interactive Narration (No. 2021WQNCX108).

References

[1] W. Guoxin, *Corporate Image Design*, Shanghai Pictorial Press, Shanghai, 2006.

[2] A. Kato, *Lectures on Museology*, Yusankaku Publishing Co., Tokyo, 1979.

[3] F. Zhenlun, "The origin and development of Chinese folk museums," *China Museum.*, vol. 4, p. 47, 1990.

[4] W. Hongjun, *Fundamentals of Chinese Museology*, Shanghai Ancient Books Publishing House, Shanghai, 2001.

[5] A. Tingshan, *Introduction to Chinese Ethnic and Folk Museums*, Forbidden City Press, Beijing, 2009.

[6] L. Zhiling, *Museum image design: Issues related to the introduction of CI strategy*, pp. 154–157, College of Arts and Museums. Beijing University, 2016.

[7] B. C. Gao, "Intangible cultural heritage as public culture," *Academic Research*, vol. 2, pp. 76-77, 2008.

[8] H. Yong, *Analysis of the Advantages and Design of Chinese Character Signs*, Hunan Normal University, 2005.

[9] J. Yingchun and G. Xiaolong, "The application of VI system in museums," *China Museum.*, vol. 12, pp. 71–73, 2003.

[10] J. Zhao and X. D. Ma, *Corporate Image Design*, Shanghai People's Publishing House, Shanghai, 2007.

[11] W. Xiao, "The application of CI system in museum management," *China Museum.*, vol. 4, pp. 36–40, 1999.

[12] Q. Jingming, *Museums and Audiences*, Tsinghua University, 2004, Master's thesis.

[13] W. Lingzhong, *The Psychology of Visual Art*, People's Art Publishing House, Beijing, 2005.

[14] Y. Shen, Q. Wu, X. Wang, and H. Bi, "Wireless sensor network energy-efficient routing techniques based on improved gear," in *2009 IEEE International Conference on Network Infrastructure and Digital Content*, pp. 114–118, Beijing, China, 2009.

[15] S. Wang, Y. J. Yan, F. P. Hu, and X. X. Qu, *Theory and application of wireless sensor networks*, Beijing University of Aeronautics and Astronautics Press, 2007.

[16] A. Zhigang, *Introduction to new network technologies*, People's Post and Telecommunications Publishing House, 2006.

[17] L. C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: semantic image segmentation with deep convolutional nets," *Atrous Convolution, and Fully Connected CRFs*, vol. 40, no. 4, pp. 834–848, 2017.

[18] M. Everingham, A. S. M. Eslami, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, "The Pascal visual object classes challenge: a retrospective," *International Journal of Computer Vision(IJCV)*, vol. 111, no. 1, pp. 98–136, 2015.

[19] V. Badrinarayanan, A. Handa, and R. Cipolla, "A deep convolutional encoder-decoder architecture for robust semantic pixel-wise labelling," 2015, https://arxiv.org/abs/1505.07293.

[20] A. Kendall, V. Badrinarayanan, and R. Cipolla, "model uncertainty in deep convolutional encoder-decoder architectures for scene understanding," 2016, https://arxiv.org/abs/1511.02680.