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Geographical Image Feature Analysis of Spiking Neural Network Considering Regional Information

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Abstract: With the rapid development of remote sensing technology and computer technology, the quality of geographic image(GI) obtained by various remote sensing image acquisition methods is getting higher and higher, and the content of image expression is more and more complex. Degree requirements are getting higher and higher. In the GI obtained by remote sensing equipment, it can be seen that the global features of urban areas have a high degree of similarity. Most of the current image retrieval methods are based on global features, and a large number of repeated streets, residential areas, and commercial areas in urban GI make it difficult to It is difficult to retrieve regional information for geographic location positioning through traditional methods. Therefore, in this paper, a GI feature retrieval method based on spiking neural network(SNN) model, after comparing the effectiveness of SNN algorithm and LM-FNN, FNN, RNN and other neural network algorithms, it is verified that spiking neurons can optimize network performance. The experiments of GI texture feature extraction and local feature retrieval show that the proposed algorithm is more feasible in GI feature analysis.

1. Introduction

With the rapid development of information technology, especially with the implementation of the digital earth plan, the processing and application of geo-geographic data have put forward higher requirements for corresponding technologies. The rapid development of remote sensing technology has made the obtained geographic pictures larger in magnitude and higher in quality. However, the current remote sensing geographic picture retrieval technology cannot meet the needs of applications. Fast and accurate retrieval of target regions from massive databases is still a challenging task [1, 2].

The research on GI feature analysis has always been the focus of scholars. For example, in the field of GI retrieval, some researchers have built a prototype of a GI fuzzy neural network retrieval system. They used texture energy and color as eigenvalues for GI retrieval and classification, and proposed a new extraction method of global texture energy descriptor, which was combined with texture color feature descriptor for GI retrieval. The same approach applies to GI classification. Experimental results show that methods using image color and texture features can achieve good results in GI classification [3]. Some scholars have proposed a fully convolutional neural network, which integrates the results of up-sampling of GI feature maps, and outputs pixel-level classification results after fusion, which improves the accuracy of semantic segmentation of images. On the basis of the fully convolutional network classification, the fully connected conditional random field is used to further optimize the classification results, and its research has achieved breakthrough results [4]. Due to the continuous development of neural networks in computer vision and other fields, the introduction of neural network algorithms into the field of geographic information to extract feature information from high-resolution images has gradually attracted more attention from researchers.

This paper firstly introduces the process of image digitization and image feature extraction in GI processing, then proposes a spiking neuron model, and analyzes the algorithm idea and algorithm implementation process of GI feature retrieval based on SNN. The simulation experiments are carried out to verify the effectiveness of the algorithm in the analysis of GI features.

2. GI Processing and SNNs

2.1. GI Processing Based on Regional Information

(1) Digital processing of images

Most of the GI obtained by the sensor are analog images, which are continuous signals and cannot be directly processed conveniently. Usually, the image is digitized by special digitizing equipment. First, the image that is continuous in time and space is discretized. This process is called sampling [5]. The sampling process is: scan the original two-dimensional image through M horizontal scan lines, and sample each scan line at the same time. Assuming that each line is sampled N times, the image that can be scanned is MXN discrete However, the extracted pixels are grayscale values of different brightness levels, which cannot be calculated and need to be quantized. Quantization is the process of expressing gray values with positive gray levels [6-7].

(2) GI feature extraction

In the classification of GI, due to the large amount of feature information of the original image features, some feature information is unclear or does not meet the classification needs of users. This shows that in the process of image classification, the continuous improvement of image feature extraction technology is particularly critical to improve the classification accuracy of GI [8]. Feature extraction is the process of data dimensionality reduction in the high-dimensional space of the image. It uses the features of the low-dimensional space to describe the high-dimensional feature information with a lot of information through transformation and other methods [9]. Feature selection is the process of picking from all the features of an image -- a group or set of features that can describe the image. The effectiveness of feature selection is directly the biggest factor affecting the classification accuracy. If the selected features are few, the accuracy of the classification accuracy will be affected, and the many features will affect the calculation speed, and the implementation is more complicated [10-11].

2.2. The Spiking Neuron Model

The human brain has large-scale parallel processing, strong fault tolerance, good association and strong adaptive ability in information processing [11]. The spiking neuron model starts from the brain information impulse transmission and biological spiking neurons, extracts a powerful information expression mechanism, and proposes a spiking IF model [12]. The IF model is a simplified phenomenological Spiking neuron model, which is a typical threshold model. The pulse waveform and amplitude of each neuron firing are constant, and its characteristic lies in the different timing of its firing [13].

The action potential of a biological neuron is an all-or-nothing response. The neuron receives the pulse signal from the presynaptic unit to form the post-synaptic potential, and the potential difference with the fluid around the cell body forms the membrane voltage; if the membrane voltage accumulates to the threshold, the action potential will be triggered and transmitted to the post-synaptic neuron, Upon completion, the neuron enters a refractory period. In a certain period of time, no matter what input stimulus is received, no more action potential will be generated [14-15].

Spiking neurons simulate the real biological neuron information transmission mechanism, so different neuron models can be obtained based on different types and different levels of neuron selection [16]. The expression describing the relationship between membrane potential and time is:

$$\partial_t \frac{dV}{dt} = -V(t) + RI(t) \tag{1}$$

where V(t) is the neuron membrane potential and ∂_t is the time constant describing the time span during which the action potential drops to zero.

$$h_j(t) = -k_\tau \ln\left(\frac{k}{\sin(e^{\ln(\theta_j(t))+\Lambda})} - 1\right) \tag{2}$$

Among them, h_j is the spike intensity of the jth neuron in the hidden layer, k and k_τ are constants, θ_j is the output of the jth neuron in the hidden layer, and Λ is a positive value.

3. GI Feature Retrieval Based on SNN

3.1. Algorithm Idea

Aiming at the problem of how to quickly and accurately retrieve images of target areas with unknown coordinates, sizes and orientations in massive GI databases, a robust GI feature retrieval method that can satisfy both accuracy and efficiency is proposed. The method first uses the gray level co-occurrence matrix to extract the texture features of the GI, and then sorts the images in the image library according to the similarity between the images to be retrieved and their texture features. In this step, the retrieval efficiency is improved by organizing the image data. After obtaining the results of index sorting, according to the order of similarity, the local features obtained by the scale-invariant feature transformation algorithm are used to match between pictures, and finally accurate retrieval results can be obtained, which ensures the accuracy and robustness of retrieval [17-18].

3.2. Algorithm Implementation

A practical system to solve the problem of GI retrieval should meet three requirements: high recall rate, the relevant geographic location images in the GI database should be retrieved, even if they only occupy a small part of the image; high precision, if the database image and query images do not belong to the same location area, then they should not match, which is important because incorrectly tagged images can waste the user's time; to be efficient, the time required to query images should be small, geoimage databases are often very large, and the expansion will contain massive amounts of data. As shown in Figure 1, according to the algorithm steps of GI retrieval, the algorithm prototype system is divided into three modules, namely offline processing module, online processing module and online retrieval module.

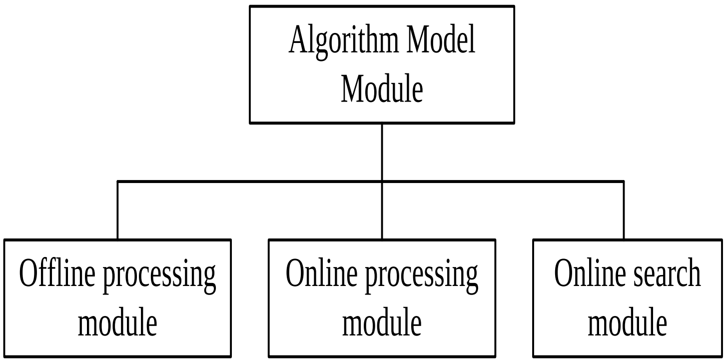

Figure 1. Algorithm model module division

Offline processing module: Through the feature extraction method in the offline processing module, the GI library will be converted into a feature database for further feature similarity matching. The feature database includes the global feature vector and local feature vector of the image library, and the gray-level co-occurrence matrix algorithm and the scale-invariant feature transformation algorithm are used respectively.

Online processing module: Its function is to compress and preprocess the original input image to be retrieved and convert it into a feature vector that can be retrieved. It also adopts gray level co-occurrence matrix and scale-invariant feature conversion algorithm.

Online retrieval module: This module includes preliminary retrieval and precise retrieval. Through preliminary retrieval, the global feature of the image, that is, the similarity of texture features, is obtained, and the data index is reordered according to the similarity. The locality-sensitive hashing algorithm is used to organize the data structure and speed up the retrieval process. Precise retrieval includes image matching and error result elimination, using the nearest neighbor classification algorithm for local feature matching, random sampling consistency algorithm for error elimination in retrieval results, and finally returning the positioning results.

4. Analysis of Algorithm Experimental Results

4.1. Comparative Analysis of Algorithm Effectiveness

In order to verify the effectiveness of the SNN, this paper selects LM-FNN, FNN, RNN and other neural networks to conduct comparative simulation experiments on Mackey-Glass time series. The experimental results are shown in Table 1. It can be seen that the SNN needs the least number of hidden layer neurons in the training process, and the neural network structure in the steady state is the most compact. At the same time, in the experimental results, the training RMSE and the testing RMSE are the smallest among the listed methods, and the network training accuracy can also be guaranteed. The comparative experiments show that the SNN achieves better generalization ability and also has the most compact network topology, indicating that the neuron algorithm proposed based on the spiking mechanism can adjust the network structure and optimize the network performance.

Table 1. Comparison results of algorithm effectiveness

Neural Networks	The number of neurons in the hidden layer	Training-RMSE	Test-RMSE	Training accuracy
spiking NN	5	0.0082	0.0124	99.37%
LM-FNN	8	0.0096	0.0163	97.51%
FNN	9	0.0145	0.0197	92.36%
RNN	12	0.0276	0.0235	87.28%

4.2. Effectiveness Experiment of Texture Feature Extraction by Gray Level Co-Occurrence Matrix

As shown in Table 2 and Figure 2, different regions of the geographic picture have different eigenvalues of the grayscale co-occurrence matrix. Through the calculation, in the entire GI, the image information generally included is divided into residential areas, forest green areas, factories, rivers, and open spaces. Among the selected GI samples, the contrast value of residential areas is 2475, the highest contrast value of factories is 3149, and the lowest contrast value of forest vegetation areas is only 382. Other eigenvalues can also be used for regional classification. For example, the dissimilarity is only 8.15 for the forest area and 54.72 for the factory area; the homogeneity value is 0.147 for the river area, but only for the factory building area. 0.0683. Each eigenvalue reflects different characteristics of the texture. For example, the contrast reflects the clarity and texture depth of the image texture; the homogeneity is used to measure the gray level uniformity of the image texture; the energy describes the intensity distribution of the image texture.

Table 2. Eigenvalues of gray-scale co-occurrence matrix in different geographic regions

	Contrast	Dissimilarity	Homogeneity	Energy	Inverse difference matrix
Residential area	2475	36.34	0.0741	0.14	0.051
Forest green area	382	8.15	0.2235	0.16	0.058
Factory	3149	54.72	0.0683	0.35	0.062
River	1063	18.33	0.147	0.39	0.067
Space	1237	26.71	0.178	0.32	0.054

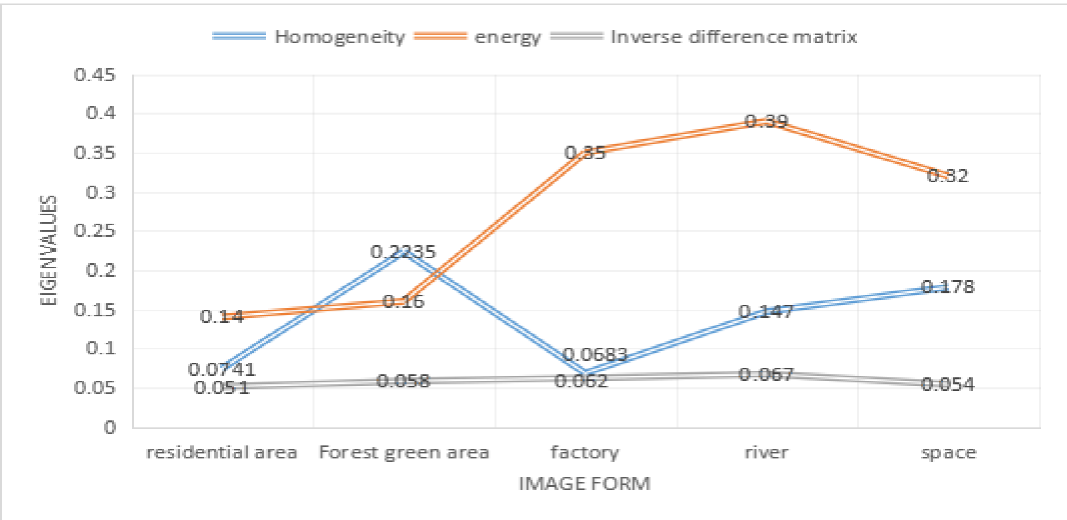

Figure 2. Homogeneity, energy, inverse difference matrices for different geographic regions

4.3. Comparative Experiment of Local Invariant Feature Matching Algorithms

In order to evaluate the efficiency of the algorithm, the retrieval time, recall and precision of the SNN algorithm proposed in this paper and the SIFT algorithm are compared. Because of the high pixel accuracy of GI and the large amount of local feature information, the processing and retrieval process will generate a large amount of calculation, resulting in a long running time, so it will take a long time to directly use local features to retrieve. The algorithm in this paper reduces the matching process of precise retrieval through preliminary retrieval, and achieves the effect of reducing retrieval time. The essence of the SIFT algorithm for GI retrieval is the matching between local invariant feature vectors. Opencv provides the BFMatcher method to find the most similar points to the sample feature points in the feature library through the brute force method. In this experiment, the SIFT algorithm feature vector Matching uses the brute force method selected. GI feature retrieval based on SNN shortens the retrieval time. Its essence lies in reordering the feature indexes in the database based on texture features before accurately retrieving local invariant feature vectors, so that the similarity with the sample image features is higher. The data of the data is sorted in the top position, and the precise retrieval time after the data structure organization is shortened. Figure 3 shows the comparison data of the efficiency and accuracy of SNN based GI retrieval and SIFT algorithm.

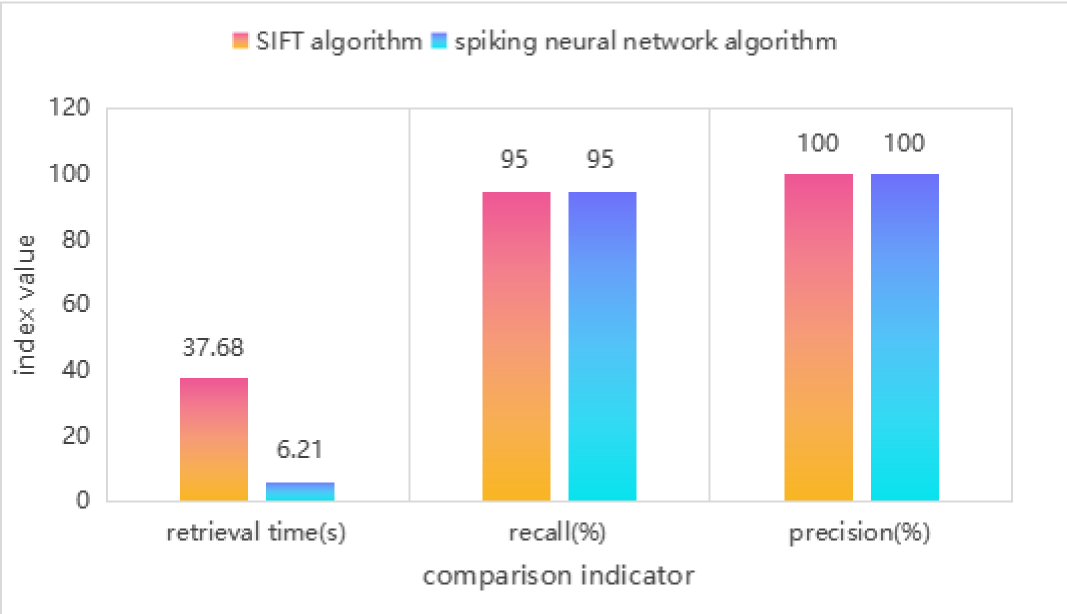

Figure 3. Comparison of algorithm feature retrieval efficiency

In the pixel size comparison, the SIFT algorithm only uses the scale-invariant feature transformation to directly retrieve the results, and the average time for each sample to find the retrieval results is 37.68s; while the algorithm in this paper combines preprocessing, preliminary retrieval and precise retrieval. The final average retrieval time is 6.21s. The retrieval precision rate of the two algorithms can reach 100%, and the recall rate can reach 95%. The experiment shows that the remaining 5% of the unretrieved samples are the cases where the images to be retrieved are forest areas.

5. Conclusion

Through the research on the current mainstream image retrieval methods, it is found that due to the unclear theme of GI, high resolution, especially the high homogeneity of street buildings in urban areas, there is currently no method that can satisfy GI retrieval at the same time. Methods for accuracy, robustness, and efficiency. Therefore, this paper introduces the SNN into the GI feature analysis, which solves the problem of the current low efficiency of GI information collection, and the simulation experiment of GI feature analysis based on the SNN shows that the algorithm can quickly obtain high-quality and high-quality images.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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