Intelligent Mining Method of New Media Art Image Features Based on Multi-scale Rule Set

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Abstract. In the feature mining of new media art images, there are always problems such as low coverage, which lead to incomplete mining data. Therefore, this paper designs an intelligent feature mining method for new media art images based on multi-scale rule sets. After the noise in the new media art image is removed by the variable window filtering algorithm based on the local pixel distribution rule, the new media art image is segmented. Design multi-scale association rule mining algorithm to realize the feature mining of new media art images. Test the performance of the design method. The test results show that the design method has high coverage, high accuracy and low average support estimation error.

Keywords: Multi-Scale Rule Set · New Media Art Image · Filtering Control Strategy · Feature Intelligent Mining

1 Introduction

In a broad sense, new media art refers to the art of using other media other than traditional media such as painting and sculpture since the 20th century, including photography, film, neon tubes, electronic mechanical devices, etc. With the invention of Apple Computer and the progress and popularization of computer programming technology [1], computer vision technology, network technology and interactive technology have gradually entered the field of art practice, making new media obtain large-scale artistic applications in computer image modification, digital video and editing, video synthesis, Flash animation and other application technologies, which makes new media art obtain a revolutionary breakthrough in language technology and image aesthetics. In the late 20th century, the narrow sense of new media art actually refers to video art. The direct meaning of the word Video refers to television, video and video [2, 3]. In its mixed use, the feature mining of new media art images becomes more difficult. Based on this background, the intelligent feature mining method of new media art images is studied.

Although there are many researchers studying image data mining technology, but for the overall image mining technology, the research of image feature mining technology is still in the initial stage. Among them, Mu Xiaodong, Bai Kun, You Xuanang and other scholars [4] proposed a remote sensing image feature extraction and classification

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method based on comparative learning method, which can fully mine high-level semantic features in remote sensing images without using data labels. Xu Yangyang, Gu Xin, Wang Annie and other scholars [5] designed an algorithm model for data fusion mining of multiple image sources in the medical field and applied it to the teaching of imaging in colleges and universities. The above methods have some problems in application, so an intelligent image feature mining method based on multi-scale rule set is proposed. On the basis of denoising and segmentation of new media art images, multi-scale rule sets are used to realize feature mining of new media art images. Experimental results show that the proposed method has high mining performance.

2 Intelligent Mining of New Media Art Image Features

2.1 New Media Art Image Denoising

The noise detection method is mainly divided into the following two steps: First, distinguish whether the pixel is non noise or may be contaminated by noise. Only processing noise points can greatly reduce the time of filtering algorithm execution. Non noise point detection in this stage is to determine whether it is likely to be contaminated by impulse noise by analyzing the gray value characteristics of pixel points according to the distribution of image gray values in the global range. In the image containing impulse salt and pepper noise, the gray value of the noise signal is shown as maximum or minimum. When formula (1) is established:

$$\xi \approx \rho_{\max} \text{or} \xi \approx \rho_{\min} \tag{1}$$

In formula (1), ξ represents the gray value of the noise signal; $\rho_{\max}$ refers to the maximum value of the image; $\rho_{\min}$ is the minimum of the image. If the gray value is close to the maximum or minimum value of the image, the current pixel is most likely a noise point. The current pixel is most likely a noise point. On the contrary, it is the signal point.

Then, the noise signal and the non noise signal are further determined among the pixels that may be polluted by the noise. For a pixel at the extreme value, it cannot be determined that it is a noise point. It may also be a detail or edge point of the image, which plays an important role in the integrity of image information. In this stage, it is mainly to analyze whether the information around the pixel of suspected noise is relevant [6]. If there is no correlation with the surrounding information, it is very likely to be a noise signal; However, if there is a large piece of suspected noise around it, it may be banded detail information.

The general filter noise detection and filtering processing [7, 8] start from the second row and second column of the image, and cannot process the pixels in the surrounding rows and columns of the image. It can be seen from the above analysis that this algorithm has a certain dependence on the elements on the left and top of the window, and in order to reduce the propagation of noise signals in the filtering process, it is necessary to process the rows and columns around the edges of the image. Therefore, this algorithm performs virtual edge processing before image processing, that is, adjusts the number of lines as shown in Formula (2):

$$\alpha' = \alpha + 2 \tag{2}$$

In formula (2), α' refers to the number of lines after adjustment; α refers to the number of original lines.

Adjust the number of columns as shown in Formula (3):

$$\beta' = \beta + 2 \tag{3}$$

In formula (3), β' refers to the number of columns after adjustment; β refers to the number of original columns.

The specific method is to use the average value of the four vertices of the original image as the pixel value of the added row and column. Filter window with small size (such as 3 × 3) When the noise density is small, it can remove the noise signal better and destroy the image details less, but it is insufficient in the environment with high noise density; Filter window with large size (such as 7 × 7, 9 × 9). It has good denoising ability, but can not protect image details, which is easy to cause image blur and loss of details. In order to balance the contradiction between image detail protection and denoising ability, the adaptive median filtering algorithm is improved on the basis of the proposed filtering method based on local pixel related information extraction rules, and the adaptive size of the filtering window is selected, that is, the 3 × 3 filtering window is selected when the noise density is small, and the 5 × 5 filtering window is selected when the noise density is large.

The filter window traverses the image, and the noise density A_j is defined as formula (4):

$$A_j = \frac{t_j}{m \times m} \times 100\% \tag{4}$$

In formula (4), t_j is the number of noise points in the current window; $m \times m$ is the filter window size, m is an odd number, and the initial value of m is set to 3.

(1) When $A_j < 50\%$ is established:
    The filtering window remains unchanged, and the median filtering operation is performed under the window whose size is $m \times m$;
(2) When $A_j \geq 50\%$ is established:
    Increase the size of the filtering window to $m = m + 1$, and then perform sorting and median operation;
(3) In order to protect image details and improve denoising ability, in actual use, $3 \leq m \leq 5$. Initialize m after each operation;
(4) When m=5, there is still $A_j \geq 50\%$, keep the original value of the center pixel output, and proceed to the next step.
(5) In order to further improve the denoising ability of the filter under the condition of high noise density, all sorting median operations are only carried out in the non noise point gray values in the current window, that is, sorting median values among all $f(x, y) \in S$ gray values.

Based on the above analysis and discussion, in order to protect more image details and improve the filter filtering ability in high noise environments, the variable window filtering algorithm flow based on local pixel distribution rules is as follows:

Step 1: Enter the image. The input size polluted by salt and pepper noise signal is X × Y, the gray value of the pixel on the image is recorded as $f(x, y)$.

Step 2: Edge processing. The average value of the pixel values of the four corners of the image is used to add virtual edges to the image.

Step 3: Noise detection. Select 3×3 The window traverses the image and detects and judges all points on the image according to the noise detection strategy. The pixel points are classified into noise N set and non noise S set. All points of pixel value $f(x, y) \in S$ are output without processing and the original value is maintained. The next step is to operate on point $f(x, y) \in N$.

Step 4: rule extraction. Define the decision rules. If the pixel information near the noise point has certain correlation, replace the noise signal according to the decision rules; If it is not satisfied, it indicates that the correlation is not significant, and the next step is to proceed.

Step 5: Adaptive variable window median filtering. Select an appropriate filtering window according to the density of noise points in the window, and sort the gray values of noise points to get the median value.

Step 6: Output the repaired image. Repeat steps 3 to 5 until the image noise is filtered and the repaired image is output.

2.2 New Media Art Image Segmentation

Design an image segmentation algorithm based on DC Unet network to implement new media art image segmentation. The DC-Unet network image segmentation model uses a self encoder structure, which is divided into four stages: encoding stage, feature fusion stage, decoding stage, and pixel classification stage. DC Unet's original inspiration comes from the characteristic of empty convolution. The output result of image segmentation is an end-to-end pixel level classification label. The output and input are required to have the same size. After multiple convolution and pooling operations in the encoding stage, the output size becomes smaller and smaller. Therefore, in the decoding stage, it is necessary to use the up sampling method to restore the size to the original input size. The up sampling generally uses the transpose convolution operation, The previous pooling operation enables each pixel to see large receptive field information. Therefore, there are two keys in the classical full convolution neural network model of image segmentation network, one is to reduce the image size by pooling operation, the other is to restore the image size by using up sampling. In the process of size change, the semantic information of the image is extracted, but there will inevitably be a lot of information loss in the scaling process, so we can make a reasonable assumption: if an operation can be designed, and the image size can also have a larger receptive field to obtain more information without pooling, then the network using this operation will certainly show a better effect.

The VGG like convolutional block is used in the encoding phase. Next, a series of cavity convolutions are carried out. Each hole convolution has different hole size, and the information of different size blocks in the image is collected respectively. Then we can get more abundant combination information by superimposing them, which is conducive to the follow-up training. Since the image segmentation is a model in which the input is equal to the output, three times of up sampling are carried out and the transpose convolution operation is adopted. At the same time, the input of each layer of transposed convolution combines the output of the down sampled corresponding position in the network. This operation is called jump connection. Through jumping connection, the low-level features extracted in the early coding stage can be combined with the high-level features extracted in the decoding stage to form a richer description of features, which is conducive to the classification of pixels later. The final classification does not use the traditional full connection layer, but also uses the convolution layer. First, the network parameters are reduced; Second, it can support image input of any size; Third, it can achieve the same effect as full connection. The final loss function uses the mainstream softmax cross entropy, which always performs well in multi category classification. The softmax cross entropy function is shown in Formula (5):

$$\mathrm{soft\,max}(M) = \frac{e^{M_l}}{\sum_{i \in n} e^{M_i}} \tag{5}$$

In formula (5), M refers to the input data; M_l represents the l-th input data; M_i represents the i th input data.

2.3 Feature Mining

Based on multi-scale rule set, a multi-scale association rule mining algorithm is designed to implement feature mining of new media art images.

The process of multi-scale data mining is divided into five stages: data preprocessing, data multi-scale, multi-scale data mining core, multi-scale representation of knowledge and evaluation and use of knowledge. It is not difficult to see that the obvious difference between the multi-scale data mining process and the traditional data mining process lies in the addition of a multi-scale data step. The multi-scale data will conceptually transform the pre processed data into the manifestation of multiple scales, thus preparing for multi-scale data mining and analysis; The core of multi-scale data mining is the core of multi-scale data mining, which is mainly based on different mining tasks and multi-scale correlation theory to conduct multi-scale data mining and analysis. The multiscale data mining process will be introduced in detail in stages.

Phase 1: Data preprocessing

The data preprocessing process is shown in Fig. 1.

Phase 2: Data multi-scale

According to the requirements of the mining task, the existing scale data is conceptually aggregated or decomposed. Here, "conceptually" means not really dividing or aggregating data, but conceptually determining whether the scale of the target scale data set in the mining task is larger or smaller than the performance scale of the current data set. The real implementation of mining still uses the existing scale data set, which is consistent with the essence of multi-scale data mining. Mining the existing single scale data set, using multi-scale data mining methods, to obtain the knowledge of the target scale data set, rather than directly mining the target scale data set [9]. If the scale of the target scale data set is larger than the performance scale of the current data set, perform the data scale upward aggregation operation to merge one or some attributes of the existing data.

If the scale of the target scale data set is smaller than the performance scale of the current data set, the data scale is decomposed downward to decompose one or some attributes of the existing data.

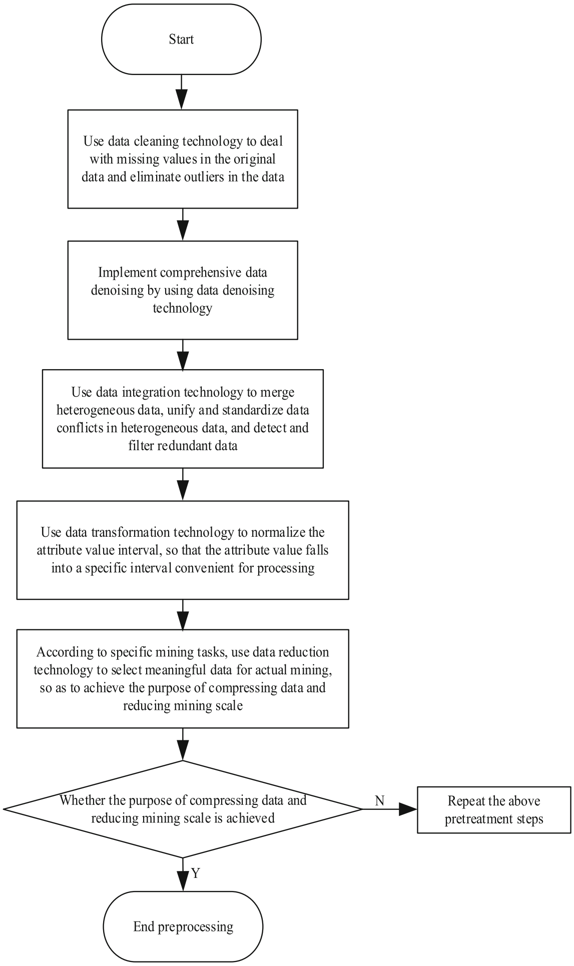

Fig. 1. Data preprocessing process

After defining the target data scale size of the data set, you can select appropriate multi-scale data mining methods according to the mining task requirements to conduct multi-scale data mining.

Phase 3: multi-scale data mining kernel

A scale up association rule mining algorithm SU-ARMA is designed. Use the association rules contained in the descendant scale data set to derive the association rules implied in the ancestor scale data set, instead of directly mining the ancestor scale data set [10]. The key of the algorithm is to use the JACARD similarity coefficient to describe the similarity between the frequent itemsets contained in each descendant scale data set, and use this similarity to simulate the similarity between the descendant scale data set itself, so as to complete the estimation of the support of some itemsets in the ancestor scale data set, and finally obtain the frequent itemsets implied in the ancestor scale data set. The jacard similarity coefficient is shown in formula (6):

$$J = \frac{\varpi \cap \theta}{\varpi \cup \theta} \tag{6}$$

In formula (6), ϖ refers to the data set of each descendant scale; θ refers to the set of frequent itemsets.

In the scale down association rule mining algorithm, the basic idea of the reciprocal distance weighting method in spatial interpolation method is mainly used, in which the domain knowledge describing the relationship between the upper and lower scale data sets plays a crucial role. Interpolation is an important method in numerical analysis, which aims to establish a complete mathematical model of the research object, and is widely used in the geographical field and graphics and image processing. The principle of image interpolation applied in graphics and image processing is similar to that of spatial interpolation applied in geography. It mainly uses image interpolation to calculate pixels with unknown gray values by using adjacent pixels with known gray values, so as to improve image resolution and quality. The mining algorithm of scale down association rules mainly draws on the reciprocal distance weighting method of spatial interpolation.

The reciprocal distance weighting method gives weight by the power of the reciprocal distance. Let Y be a series of observation points in the region, as shown in Formula (7).

$$Y = \{y1, y2, \cdots, y_m\} \tag{7}$$

In Formula (7), y_m refers to the m th observation point.

Let Q be the corresponding set of observations, as shown in Formula (8).

$$Q = \{q(y_1), q(y_2), \cdots, q(y_m)\} \tag{8}$$

In Formula (8), $q(y_m)$ refers to the m observation value.

The value $q(y_0)$ at point y_0 to be inserted can be estimated by a linear combination, as shown in Formula (9):

$$q(y_0) = \sum_{j=1}^{m} v_j q(y_j) \tag{9}$$

In Formula (9), v_j represents the weight of the j th observation value.

At this point, the mining of new media art image features was completed.

If the data scale of the target data set is large, the scale up data mining method is selected; If the data scale of the target scale data set is small, the scale down data mining method is selected.

Phase 4: Multi scale representation of knowledge

The mining results obtained from the multi-scale data mining kernel have multi-scale characteristics. The task of this stage is to show these knowledge in an orderly and logical way, and to show the multi-scale characteristics of these knowledge as much as possible. The current knowledge representation methods include natural language representation, formal logic representation, frame representation, etc. These methods all have substantial theoretical basis. At this stage, it can choose a knowledge representation method suitable for specific mining tasks according to the advantages and disadvantages of different knowledge representation methods, and combine multi-scale theory to comprehensively display the knowledge of multiple data scales in the mining results. Compared with traditional knowledge representation, this stage is more hierarchical, more expressive, and easier for users to understand and analyze data at multiple scales.

Phase 5: Evaluation and Use

Finally, multi-scale knowledge is handed over to experts, who judge the availability and effectiveness of knowledge based on domain knowledge and methods to form a result document to guide users to make multi-scale decisions. Based on the above analysis, the new media art image feature intelligent mining model based on multi-scale rule set designed in this paper is summarized as Fig. 2.

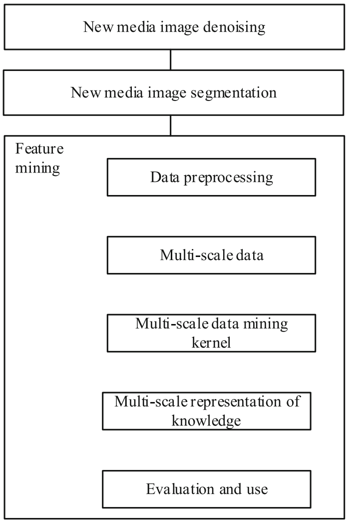

Fig. 2. Design algorithm model

3 Experimental Test

3.1 Experimental Data Set

For the new media art image feature intelligent mining method designed based on multi-scale rule set, it is tested through experiments. The experimental data sets used are three movie resource sets, as shown in Table 1.

The design method is used to intelligently mine the image features of the experimental data set. At the same time, the two methods mentioned in the introduction are used as comparative experiment methods to conduct comparative experiments, which are represented by Method 1 and Method 2 respectively.

Table 1. Details of the experimental data set

Serial number:	Project	Data
Data set 1	Movie type	Comedy
	Number of films	102
	Data set size	1524 GB
Data set 2	Movie type	Romantic love
	Number of films	59
	Data set size	853 GB
Data set 3	Movie type	Science fiction
	Number of films	62
	Data set size	923 GB

3.2 Experimental Environment

The running environment of the experiment is Lenovo M7300 desktop computer, CPU Pentium 3.40 GHz, 4G memory, Windows 7 operating system; The data used in the experiment is stored in ORACLE 10g database system, and PL/SQL tools are used to extract, clean and transform the population data in Oracle database; Select the open source Octave to implement scale up and scale down association rule mining algorithms, and complete the statistics and analysis of experimental results.

3.3 Evaluation Criteria for Experimental Results

In order to verify the correctness of the design method, 2100 GB of data were selected from three film resource sets for testing, and 9 groups were numbered from 500 GB to 2100 GB, with 200 GB as the interval, to test the coverage, accuracy and average support estimation error.

Among them, coverage represents the proportion of mining results covering the real frequent item set in the target scale data set; The precision reflects the influence of false positive term set and false negative term set on the accuracy of experimental results; The average support estimation error is the average of the support estimation error of frequent itemsets in the experimental results of the algorithm.

3.4 Experimental Results

The coverage test results of the three methods are shown in Table 2.

According to the test results in Table 2, with the increase of data volume, the coverage of the three methods has decreased to some extent. However, the maximum coverage rate of the design method of the design method can reach 97.25%, and the overall coverage rate is greater than 90%. Compared with the two comparison methods, the performance of the design method is more excellent, indicating that the design method has good coverage performance.

Table 2. Coverage Test Results

Serial number	Data volume (GB)	Coverage (%)		
		Design method	Method 1	Method 2
1	500	97.25	92.30	89.63
2	700	95.63	91.27	88.74
3	900	94.32	89.62	88.21
4	1100	93.57	88.51	87.14
5	1300	93.01	88.02	87.02
6	1500	92.84	87.62	86.41
7	1700	92.36	87.41	86.20
8	1900	92.01	86.92	85.96
9	2100	91.58	85.25	85.41

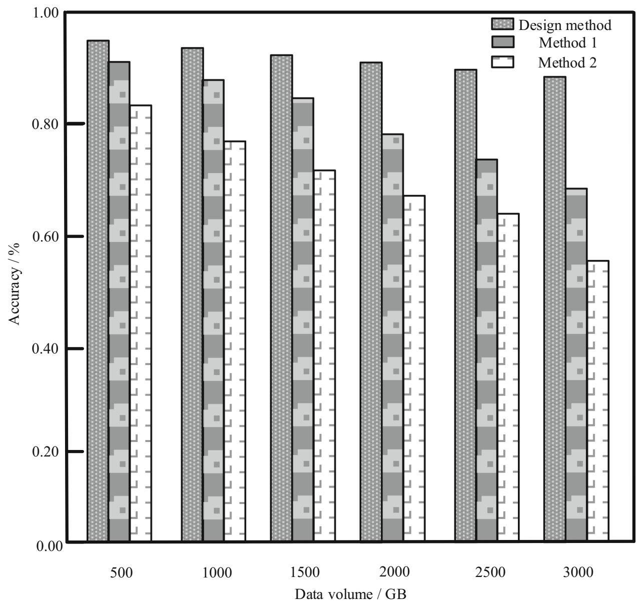

Fig. 3. Accuracy Test Results

The accuracy test results of the three methods are shown in Fig. 3.

The test results in Fig. 3 show that the accuracy of the design method can reach 0.965 at the highest and 0.895 at the lowest, which is higher than 0.89 on the whole. The accuracy is far higher than that of the two comparison methods, which proves that the design method has a high accuracy in image feature intelligent mining.

The average support estimation error test results of the three methods are shown in Fig. 4.

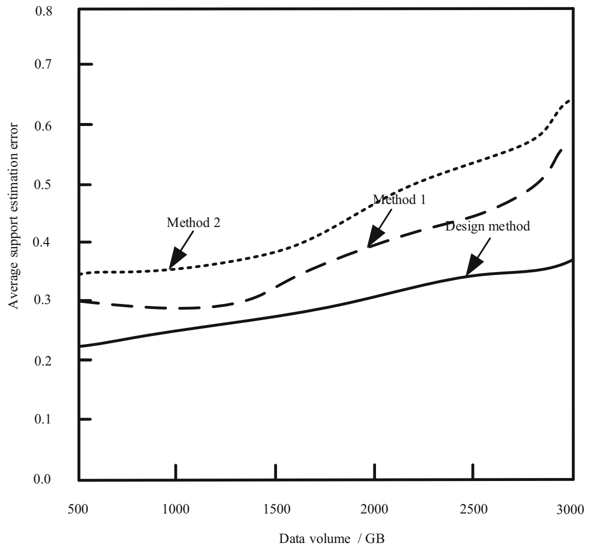

Fig. 4. Test Results of Average Support Estimation Error

Figure 4 shows that when using the design method for image feature intelligent mining, the maximum average support estimation error of the design method is only 0.34, while the average support estimation error of the two comparison methods is higher than that of the design method, indicating that the overall average support estimation error of the design method is low, which proves that the mining performance of the design method is good.

4 Conclusion

In the age of big data, data is wealth and knowledge is treasure. In the future, the attention and research on data mining will remain on the rise. The new media art image feature intelligent mining method designed based on multi-scale rule set realizes the construction of multi-scale data mining process framework, and designs multi-scale association rule mining scale up and scale down extrapolation methods to achieve high coverage and accuracy and low average support estimation error, and has achieved certain research results.

However, for multi-scale data mining, no matter in theory or method, there are still many directions that need to be further studied and expanded, which is the focus of our next work.

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