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Prototype Algorithm: Number Chain Features in Spatial Similarity Calculation of Time-Series Graph Sources

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***Abstract*—In this paper, we propose a method to calculate spatial semantic similarity based on sampled same-area time-series images. First, we preprocess the corpus data containing spatial information, then we project the coordinates in the preprocessed corpus data to obtain the actual spatial ranges, then we determine the contextual annotations of geographical feature gestures in the time-series images and perform comparison sampling, and finally we calculate the similarity between the coordinates of the overall same-area time-series image geo-corpus The similarity is evaluated for each two nodes in the set of the overall same-region geo-serial corpus. This paper identifies the causes of data noise and interpretation bias arising from the migration process of geographic data in time-series images, which effectively complements the traditional natural semantic similarity model and improves the effectiveness of intelligent geographic information retrieval and ancient landscape painting verification.**

Keywords-spatial semantic similarity; number chain feature; geographic evidence-based; spatial humanities; recommended tag

I. Introduction

This study constructs a model that can measure the spatial semantic similarity by mining the spatial semantic similarity relationship between coordinate feature gestures. It outperforms the traditional textual similarity model and geospatial similarity model in terms of integrating spatial relevance and textual relevance. Using the geo-evidence-based thinking and spatial perception methods of spatial humanities to understand the trajectory of human movement in geographic space in ancient landscape paintings, we propose a new research perspective on the interpretation and reconstruction of natural language of images, and discover the causes of data noise and interpretation bias generated by the geo-data migration process in time-series images. The research findings effectively complement the traditional natural semantic similarity model, effectively improve intelligent geographic information retrieval and ancient landscape appreciation and identification, and make a systematic accuracy guarantee for accurate, intuitive and scientific reasoning of subjective cartographic image interpretation.

The second part of the article analyzes the existing geographic image interpretation techniques and presents the motivation of this paper; the third part proposes a model for spatial interpretation of graph scenarios; the fourth part proposes a method for calculating the spatial semantic similarity of sampled same-area time-series images; the fifth part conducts an experiment on same-area time-series image interpretation using the pinnacle of Chinese landscape painting, "Dwelling in the Fuchun Mountains" and its copied version as an example; the sixth and seventh parts discuss and conclude the article.

II. Background

This study is related to the technical field of geographic information image interpretation and implicit number chain mining, and specifically to a spatial semantic similarity calculation method based on same-region time-series image sampling. In the current intersection of computer graphics and remote sensing image interpretation research, how to calculate the association relationship between text semantics and image semantics is a key part of solving the problem of spatial location co-interpretation in images. In the prior arts, generic word similarity models are obtained using large text corpus and deep learning training methods, such as Word2Vec model from Google [1] and Fast text model from Facebook [2]. The aforementioned models perform well on general texts, but when it comes to dealing with corpora containing spatial relational information, these models perform poorly, as evidenced by the inability to actually obtain the spatial semantic relations of words. On the other hand, Geographical Information Retrieval [3], when dealing with the similarity of spatial information, usually uses the method of calculating the textual similarity and spatial similarity of spatial information separately, and finally weighting the two together. However, such an approach essentially does not consider the deeply hidden information in the image, or the sparse key information in the spatial context as a whole, and therefore cannot be studied when dealing with images of geographic information that are vague, unclear, and understood as "non-scientific" records.

As mentioned earlier, the traditional natural semantic similarity model is inadequate in the study and application of the problem involving fuzzy image decoding and implicit number chain mining in spatial information, and the traditional geographic information retrieval system is inadequate in handling information with fuzzy topics, that is, the methods in the prior art have the technical problem of insufficient accuracy in handling information containing spatial relationship information and fuzzy topics.

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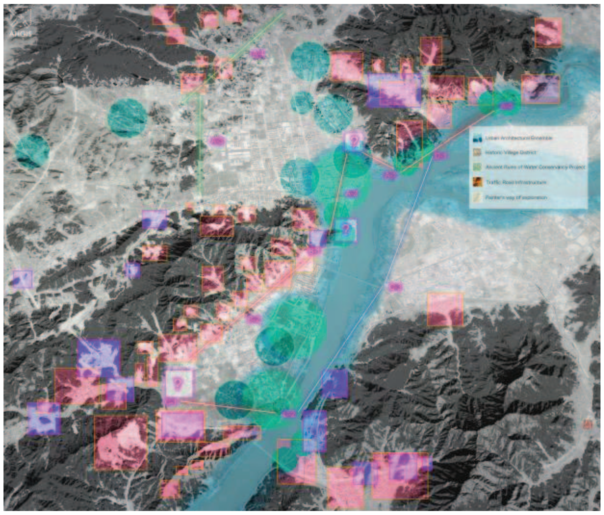

Figure 1. Destruction and Coverage of Mountains in the Process of Urban Infrastructure Construction

III. IMAGE SCENARIO SPACE INTERPRETATION

From this, we propose a reference model for Image Scenario Space Interpretation (ISSI) with the reference of OSI model [4]. The concepts of the first and layers are as follows:

A. *The first layer: physical layer*

In the ISSI model, the physical layer is the most basic underlying layer of the reference model and the first layer of the ISSI model. The main function of the physical layer is to adapt and topology by using spatial-temporal tags on the basis of full access to multifaceted geographic information data and heterogeneous social images, data, models and other resources. Among them, transmission media and link standards provide physical connections for the data link layer to achieve transparent transmission of bit streams. The physical layer has the above functions and emphasizes alignment, elimination and validity evaluation after data acquisition to guarantee the rate and quality in data transmission.

B. *The second layer: knowledge data link layer*

The Knowledge Data Link Layer (KDL) is the second layer of the ISSI model, which is responsible for establishing knowledge data and managing the links between knowledge association nodes to describe the condensation process after the subjective understanding of the abstract laws of knowledge logic and objective observation, and the computational model decoding. The link assignment of all data information received in this layer corresponds to the objective encryption and decryption logic in graph scenario recording technology and the subjective deviation and scenario decoding deduction in the process of graph space recording, respectively.

In the process of computational decoding, there are different interpretations, encryptions, interferences, noises, deviations, variants, and corruptions among the time-series images, leading to the unreliability of relying solely on physical links for theme interpretation. Therefore the main function of the ISSI model is to change the physical (cognitive logic) lines with errors into data (traversal laws) links without errors through error control and traffic control methods based on the content distribution protocols provided at the physical layer, i.e., to provide a reliable method of transmitting data through knowledge reorganization.

In view of this, this study provides a method for calculating spatial semantic similarity based on same-region temporal image sampling to solve, or at least partially solve, the technical problem of insufficient accuracy of the methods in the prior art when dealing with information containing spatial relationship information and subject ambiguity.

IV. METHOD

To solve the above technical problems, this study discusses a method for calculating spatial semantic similarity based on same-area time-series image sampling, including the following steps: 1) spatial analysis and pre-processing of complex image scenarios; 2) matching the actual geographic geo-spatial ranges; 3) realizing one-to-one correspondence between the words in the image corpus data and the projected spatial coordinates; and 4) realizing the services provided to the resource sub-networks at the upper and lower ends.

A. *Pre-processing of pre-sampled data and algorithmic reserve:*

1) The corpus data containing spatial information is preprocessed, where the spatial information is GPS coordinates;
2) The GPS coordinates of the spatial data in the pre-processed image corpus are projected using the preset cosine similarity [5], Jaccard similarity [6], perceptual hash algorithm [7], histogram mask[8] and area projection algorithms to obtain the actual spatial extent, and the words in the corpus data correspond to the projected spatial coordinates one by one;
3) Determine the contextual annotation correspondence according to the distribution density, area size, sampling features, and humanities information of the mapped image spatial coordinates, and sample the image slices by a preset scale adaptation under the contextual annotation correspondence, and obtain the sampling results;
4) The image slicing sampling results include contextual graph scenarios with different adaptation ratios and the set of spatial feature poses corresponding to each contextual temporal slice control group, and the set of spatial feature poses corresponding to each contextual graph scenario constitutes the overall set of spatial feature poses;
5) Similarity calculation is performed for each group of corresponding feature pose data clusters in the overall spatial feature pose collection.

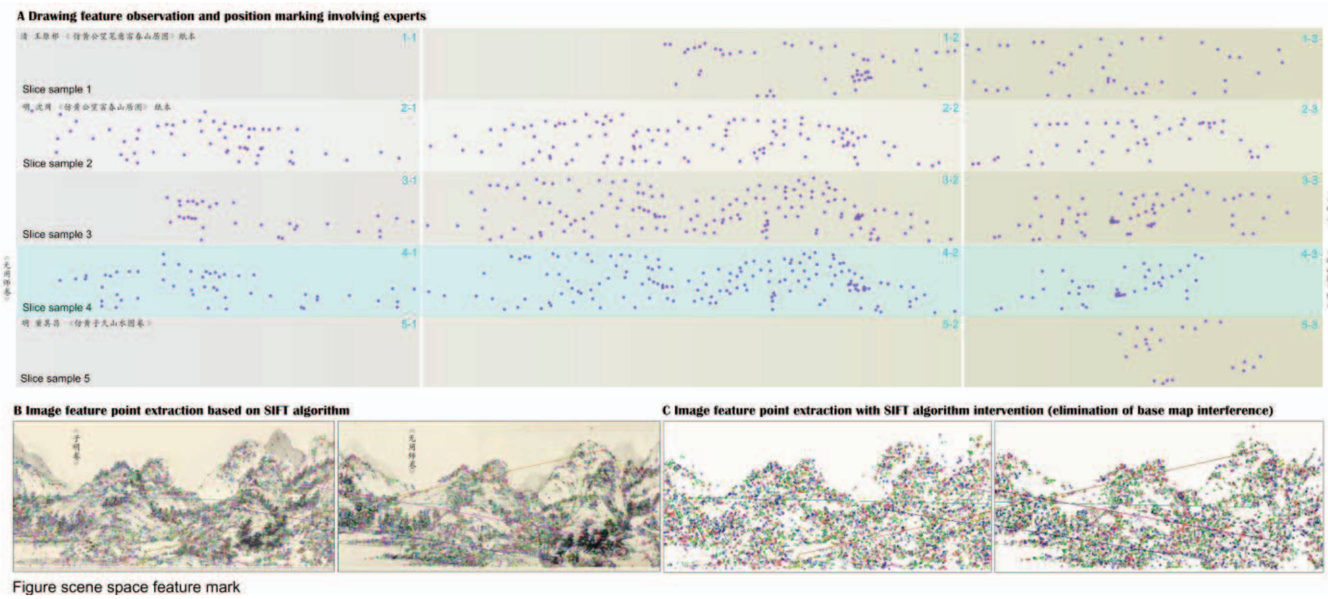

Figure 2. Composite extraction of marked points at all levels such as mountains, water systems, habitats, roads, etc.

B. Mid-term algorithm implementation:

1) A multimodal algorithm is used to process the corpus data containing spatial information in the form of 'feature pose - coordinates' by word separation and obtain data in the format of 'feature pose - coordinates'.
2) The Behrmann projection method [9] is used to project the GPS coordinates in the pre-processed corpus data, and the specific equation of the projection is:

$$x = \frac{x' \times \pi}{180} cos\frac{\pi}{6} \quad (1)$$

$$y = \sin\left(\frac{y' \times \pi}{180}\right) \times sec\frac{\pi}{6} \quad (2)$$

where (x', y') denotes the GPS coordinates before the projection transformation and (x, y) are the coordinates after the Behrmann projection transformation.
3) Find the maximum and minimum values from all the projected spatial coordinates and determine a minimum external rectangle based on the maximum and minimum values of the spatial coordinates;
4) Set the contextual timing slice control group, start sampling from the bottom left corner of the smallest outer rectangle, and record the spatial data contained in the spatial range corresponding to the contextual timing slice control group when sampling.

C. Validity evaluation of mid-term graph data slicing:

1) Sampling in the horizontal direction according to the preset length, then sampling in the vertical direction according to the preset length, and recording the words contained in the spatial range corresponding to the contextual temporal slice control group when sampling, until the sampling of the whole minimum outer rectangle is completed and the sampling results are obtained, where the collection set of the whole corpus C is C:{$d_1, d_2 \ldots\ldots d_n$}, and the set of words contained in each contextual temporal slice control group d_i is d_i:{$w_1, w_2 \ldots\ldots w_n$} [10]. By varying the size of the spatial contextual slicing control group d for calculation, the spatial semantic similarity of words at different scales can be obtained, and then the query, ranking and clustering tasks of spatial semantic similarity can be performed at specific scales or cross scales.
2) A minimum outer rectangle can be determined according to the extremes of the projected spatial coordinates, thus ensuring that all projected coordinates are contained within the rectangle. Then, the design of the context-controlled slice is carried out according to the minimum outer rectangle. Specifically, in a square d with side length x in space, the contextual timing slice control group is sampled from the lower left corner of the whole rectangle range, and the system records the words contained in the space range corresponding to the timing slice control group when sampling. After completing one recording, the temporal slice control group moves s lengths in the horizontal direction to start the second recording. When it moves to the end of a row, it moves s length in the vertical direction to start sampling in the second row until all the sampling in the whole rectangular range is finished. By varying the size of the spatial contextual slicing control group d for calculation, the spatial semantic similarity of words at different scales can be obtained, and then the query, ranking and clustering tasks of spatial semantic

similarity can be performed at specific scales or cross scales.

3) Graph data slicing processing and calculation specifications specifically include: Two terms are taken from the whole set of coordinates W of spatial data; the following formula is used to calculate the spatial semantic similarity of the two terms:

$$s - SIM_{w_1 w_2} = \frac{\sum d_{w_1 \cap w_2}}{\sum d_{w_1} + \sum d_{w_2} - \sum d_{w_1 \cap w_2}} \quad (3)$$

Among them, $s - SIM_{w_1 w_2}$ denotes the spatial semantic similarity of the words w_1 and w_2. $\sum d_{w_1 \cap w_2}$ denotes the number of spatial time slice control groups that contain both w_1 and w_2, denotes the number of spatial time slice control groups that contain w_1, and denotes the number of spatial time slice control groups that contain w_2. After that, said method also includes: constructing a spatial semantic similarity model by saving all the word pairs as keys and the spatial semantic similarity of each word pair as a value in the form of Key-Value.

D. Provide resource services to the upper and lower subnets:

The goal can be abstractly described as to further manage the data communication in the network, control the forwarding of information between the data link layer and the transport layer, establish, maintain and terminate connections to the network, and deliver data from the source to the destination (point-to-point) through a number of intermediate nodes, thus providing the most basic end-to-end data transmission service to the transport layer, on top of the function of delivering data frames between two adjacent endpoints provided by the data link layer.

Specifically in this study, the data at the data link layer of the geographic features are converted into sparsely distributed location position data packets after being managed by the DEM, and then the information is transmitted from one computational data module to another without loss through the control of path selection (fitness target), segment combination (travel path constraint), sequence (temporal tagging), and approach/exit routing (different data linking mechanisms).

The associated, adjacent, and interlinked data sets provided by the data link layer are transmitted to a framework with time, geography, and society as multi-way prisms, further managing the data interactions in the framework, guiding image mimicry, data mimicry, and information attribution between the data link layer and the transmission layer, establishing, consolidating, and destroying the connections between them, deepening the computational model from source-side control to the intervention, adjustment, and correction of several intermediate nodes, thus identifying the path between the encrypted information and decryptable data through path selection, semantic clustering, spatial-temporal order, principal component analysis, and other controlled ones, and achieving overall extraction, encapsulation, and transmission.

V. Evaluation

In order to better illustrate the research experiment, the calculation method herein is described in detail below with a specific example. In order to more clearly illustrate the technical solutions in the embodiments or prior art of the present invention, the accompanying drawings that need to be used in the description of the embodiments or prior art are briefly described below, and the accompanying drawings in the following description are experimental examples in the course of the present study.

To achieve the above purpose, the experimental objectives are as follows: Based on the need of spatial semantic similarity calculation of georeferenced data and same-region temporal image sampling, the spatial semantic similarity of the same data package at different spatial scales is calculated by adjusting the parameters and changing the size of the spatial control spatial temporal slice control group, which is conducive to deciphering the spatial semantic similarity within the same scale, or different scales for comparison, analysis, ranking, and clustering. It is superior to the traditional text similarity model and geospatial similarity model in terms of comprehensive consideration of spatial relevance and ecological relevance of number chains, and effectively complements the natural semantic similarity model in the traditional image interpretation link, and effectively improves the accuracy of intelligent geographic information retrieval and recommendation evaluation.

A. Experiment 1: Evaluation of accuracy of time-series landscape image drawing in the same region

1) *Hypothesis 1* : the more backward the copied version is, the less similar it is to the original version; the sample generation time sequence can be compared by the phase performance of the image with the original version.
2) *Evaluation indicators:*
   a) *Cosine similarity:* Cosine similarity measures the similarity between two vectors by measuring the cosine of the angle between them and is applicable to the comparison of vectors of any dimension. The cosine value between two vectors can be found by the Euclidean dot product formula.

$$\mathbf{a} \cdot \mathbf{b} = \| \mathbf{a} \| \| \mathbf{b} \| \cos\theta \quad (4)$$

$$\boldsymbol{\cos(\theta)} = \frac{\boldsymbol{A \cdot B}}{\| \boldsymbol{A} \| \| \boldsymbol{B} \|} = \frac{\sum_{i=1}^{n} \boldsymbol{A_i \times B_i}}{\sqrt{\sum_{i=1}^{n} (\boldsymbol{A_i})^2} \times \sqrt{\sum_{i=1}^{n} (\boldsymbol{B_i})^2}} \quad \mathbf{(5)}$$

Given two attribute vector sums, the remaining string similarity is given by the dot product and vector length, as shown in Equation (2). where represent each component of the vector sum, respectively.

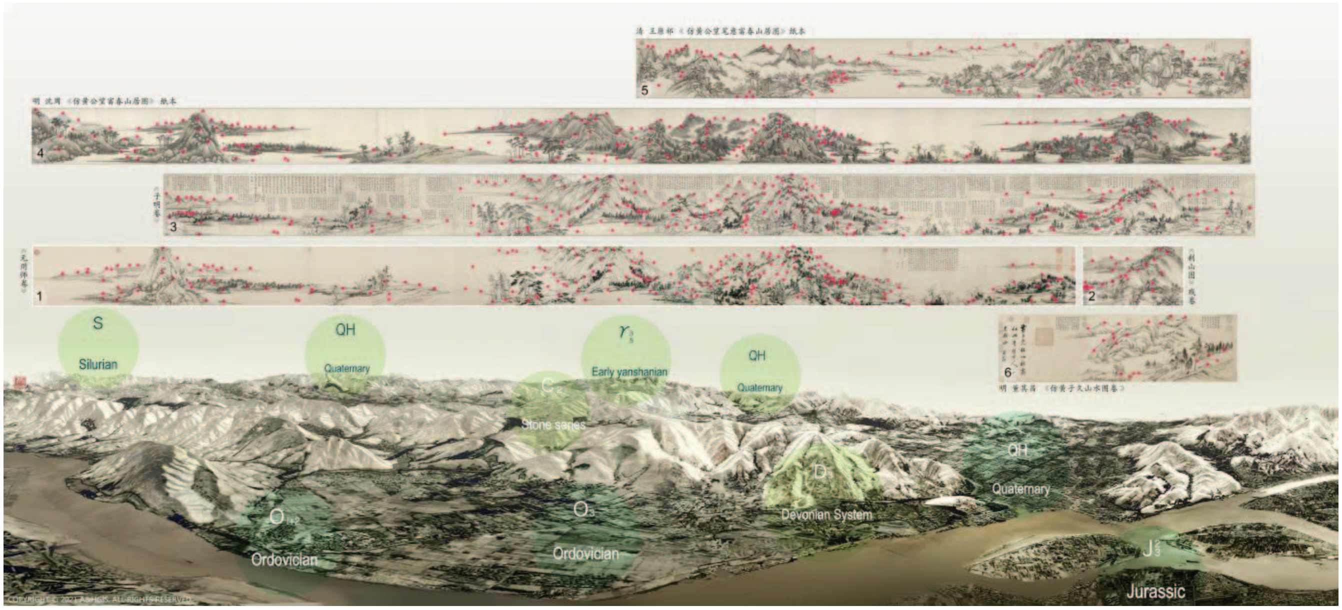

Figure 3. An analysis of the position of the Fuchun Daling images in different versions of Yuan, Ming and Qing dynasties

b) *Perceptual Hash Algorithm:* Perceptual Hash Algorithm (PHA) is a hashing algorithm to calculate the similarity of images. The algorithm calculates the similarity by reducing the size, simplifying the color, calculating and reducing the DCT (Discrete Cosine Transform), calculating the average value, calculating the hash value, comparing the Hamming distance and other steps, independent of the height and width, brightness and color of the image.

c) *Histogram similarity:* the relationship between two images is analyzed by the pixel distribution of the images. Firstly, histogram data are collected for the sample images, the histogram of the collected images are normalized, and the histogram data are calculated using the Barclay's coefficient algorithm to obtain similarity values.

3) *Experimental procedure:*

a) *Experimental materials:* "Dwelling in the Fuchun Mountains (the original scroll) ", "Dwelling in the Fuchun Mountains (oopied by Ziming), and "Dwelling in the Fuchun Mountains (copied by Shen Zhou)" HD digital image slices. The images were adjusted to black and white images by Photoshop, and the noise such as inscriptions, seals, and small breaks in the landscape paintings were removed, and all images were resized to 1920 ×1080 and saved as JPG format.

b) *Experimental method:* Using the image similarity algorithm, the same typical feature area of the Zi Ming volume, Shen Zhou volume and the original volume was subjected to similarity calculation.

c) Using Python 3.10 programming, we read in the corresponding feature area images of different versions of ancient paintings, call the above-mentioned multiple algorithms, and calculate the image similarity. The combined use of multiple methods can make up for the defects of a single image similarity algorithm and get a more reasonable similarity taking value.

4) *Experimental results*: The calculation results are shown in the following chart. As can be seen from the chart, the similarity between Shen Zhou volume and the original version is lower than the similarity between Zi Ming volume and the original version by the comparison of feature areas, which is in line with the temporal characteristics that the similarity of landscape images decreases with the process of copying in circulation. The original hypothesis is valid.

Table 1. Similarity of corresponding feature areas of different versions of ancient paintings

Frag.	Version	pHash	Hist Sim	Cos Sim	Average
1	Zhou Shen	0.8906	0.5704	0.8930	0.7847
	Ziming	0.9688	0.8746	0.9050	0.9161
	Origin	1.0000	1.0000	1.0000	1.0000
2	Zhou Shen	0.9375	0.5074	0.8790	0.7746
	Ziming	0.9688	0.7078	0.8730	0.8499
	Origin	1.0000	1.0000	1.0000	1.0000
3	Zhou Shen	0.8594	0.5724	0.8380	0.7566
	Ziming	0.9531	0.6338	0.8830	0.8233
	Origin	1.0000	1.0000	1.0000	1.0000

B. Experiment 2: Comparison of microscopic differences in landscape images

1) *Hypothesis*:

Since in ancient landscape painting, the painter usually needs to use ink to outline the image repeatedly, different painting strokes will produce different characteristics of ink shades. In the area repeatedly outlined by the painter, the color difference between a certain pixel point and the immediately adjacent pixel point is smaller; in the area outlined by one stroke of the painter, the color difference between a certain pixel point and the immediately adjacent pixel point is larger.

In computer vision, the points along which the gray level of the image changes in all directions are called corner points of the image [11]. The basic idea of the corner point detection algorithm is to use a fixed window to slide in any direction on the image and compare the degree of grayscale change of the pixels in the window between the two cases before and after the sliding. If there is a slide in any direction with a large grayscale change, then we can assume that there is a corner point in the window.

Therefore, this paper proposes hypothesis: through the corner point detection algorithm, we can roughly extract the microscopic brushstroke features in ancient Chinese landscape paintings. The proposed hypothesis is based on the principle that if the ancient painting is the original version, there will be a large number of repeated outlines of the same area during the painting process, and the number of extractable corner points is small; while if the ancient painting is a copy version, the copyist usually follows the original version and draws the target object in one stroke, and the number of extractable corner points is large.

2) *Detection methods*:

a) *Harris algorithm:* Harris is the most classic corner point detection algorithm, which can achieve precise positioning of half-pixels in the image and is very widely used. Its principle [12] is to calculate the directional gradient, and then determine whether it is maximum according to a specific threshold, and finally determine the corner point.

b) *FAST algorithm:* FAST (Features from accelerated segment test) [13] is an algorithm for corner point detection, which is defined as having enough pixel points in the field around the pixel point that are in a different region from the point.

c) *SIFT algorithm:* SIFT (Scale Invariant Feature Transform) algorithm [14] is an efficient region detection algorithm. Its main idea is to find the extreme points in the scale space, then filter the extreme points to find the stable feature points, and finally extract the local features of the image around each stable feature point to form local descriptors.

3) *Experimental procedure*:

a) *Experimental materials:* In this section, high-definition digital images of the corresponding areas of the "Dwelling in the Fuchun Mountains" Ziming version, Shen Zhou version and the original version were used for comparison, and the sample images were adjusted to equal length and consistent size grayscale image fragments in advance.

b) *Experimental method:* Through a variety of corner point extraction algorithms, we extract the features of brush stroke intersection, break point and turning point produced by different drawing methods in the painting, and calculate the number of corner points compared to each image.

c) Using Python 3.10 programming, we read in each sample image, call multiple algorithms from the Opencv library to detect the sample, and finally return the feature point labeled image and the number of feature points.

4) *Experimental results:*

Table 1 Comparison of the number of characteristic points of ancient painting strokes (ratio to Origin version) in different versions

Version	SIFT	FAST	Harris	Average
Zhou Shen	1.2213	1.2046	1.0015	1.1622
Ziming	1.0168	1.4441	1.0115	1.1575
Original	1	1	1	1

a) The experimental results are shown in the table. In the detection of the number of brushstroke feature points, the number of brushstroke feature points of Shen Zhou volume and Zi Ming volume is significantly more than that of the original version of Dwelling in the Fuchun Mountains (useless master - leftover mountain volume). The difference between the Shen Zhou volume and the Zi Ming volume is smaller, and the feature points of the Shen Zhou volume are slightly more than the feature points of the Zi Ming volume.

b) In the above corner point detection algorithm, the principle of the algorithm is to detect the difference between a certain pixel and multiple surrounding pixels, and if the difference is large, it is more likely to be detected as a corner point. Therefore, when the author of the original painting repeatedly sketches a certain area, the number of corner points that can be detected will be correspondingly smaller under the control of the threshold value due to the change of ink color intensity; while the copied version, with the original version as a reference, is less likely to repeatedly sketch and modify the image, and more likely to be shaped by one stroke, with relatively clean and neat brush strokes, so more feature points can be detected.

c) The above experimental results are basically consistent with the original hypothesis.

d) Although Harris algorithm, SIFT algorithm and FAST algorithm can extract the brushstroke feature points of ancient paintings, the SIFT algorithm can maintain a certain Chengdu while stability for noisy ancient paintings due to its stronger scale robustness and distinguishability [15], while the other two methods are sensitive to scale and perform poorly in geometric scale non-deformation, therefore, in the follow-up study, for Therefore, in the evaluation of image stroke feature points, the weight of the SIFT algorithm results should be moderately increased, instead of directly taking the average of the three algorithms, in order to improve the accuracy of the evaluation of stroke feature points.

VI. Discussion

The experimental part of this paper considers the spatial feature pose similarity and spatial similarity in geographic information as a whole, uses the same region time-series images to sample in the corpus with spatial information, calculates the co-occurrence probability of similar spatial pose in different map sources, calculates more accurate spatial semantic similarity between different dimensions, different periods and different mapping targets at different scales, which is convenient to compare with the semantic similarity obtained by text semantic The multi-scale feature helps to discover the correlation of spatial feature pose with the change of spatial scale, and the change law, which is helpful to discover the implicit encryption information in the graph scenario space, and explain how the decoded information is re-encrypted through the logic of number chain ecology, and identify its spatial distribution law.

In order to make the purpose, technical solution and advantages of the embodiment of the present invention clearer, the technical solution in the embodiment of the present invention will be described clearly and completely below in combination with the accompanying drawings in the embodiment of the present invention. The technical scheme and implementation steps include:1) taking the same region time-series image with explicit geographic information as the object, completing the label data as the base coordinate database, and firstly transforming the data; 2) performing Behrmann projection on the geographic data corresponding to the pre-processed corpus data, i.e. GPS coordinates, and furthermore, determining the minimum outer rectangular range of all coordinates as the sampling range ; 3) In the sampling range, the area is designed as a rectangular slice for the control sampling temporal slice control group (i.e., the contextual control slice group), and the data is extracted and stored from the full domain of the slice for one sampling. After completing one sampling, and so on, until the spatial range corresponding to the corpus in the whole experimental sample slices are sampled, the sampling work is completed. At this point, the same-region temporal image sampling set of the whole corpus is obtained; 4) for each sample acquisition at each scale, the corresponding spatial distribution pose of each group is calculated for inference calculation.

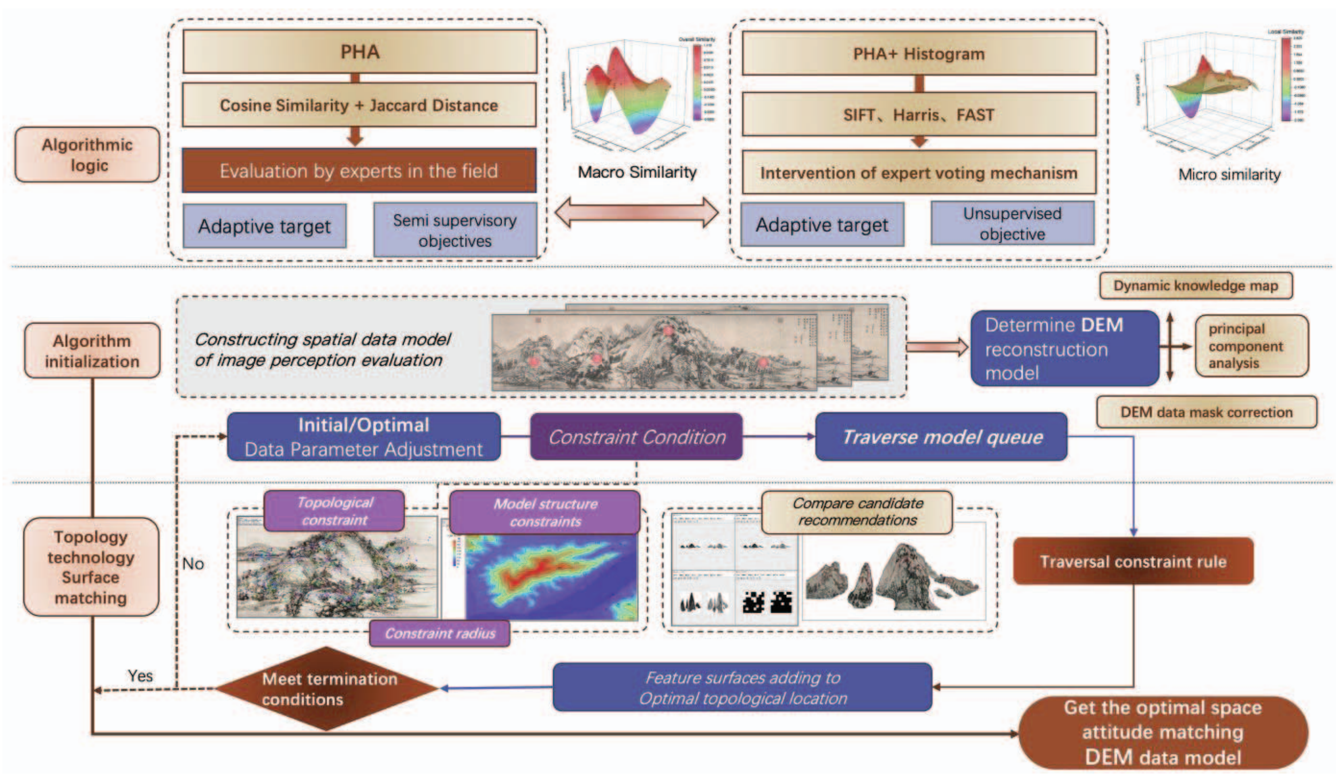

Figure 4. Reconstruction of Accurate DEM Data Model with Multiple Constraints

VII. Conclusion

In terms of comprehensive consideration of spatial relevance and number chain ecological relevance, this study outperforms the traditional text similarity model and geospatial similarity model, and effectively complements the natural semantic similarity model in the traditional image decoding session, which can effectively improve the accuracy of intelligent geographic information retrieval and recommendation evaluation. After identifying the preferred implementations in hybrid image resources and obtaining extremely strong implicit relationship mining capabilities, additional changes and modifications can be made to these implementations. Obviously, scholars in cross-disciplinary research fields can make various changes and variations to this method implementation case, and the paradigm innovation of this study intends to promote more research changes and logical reuse to obtain more discoveries.

By analyzing the change rate (first-order derivative) of spatial semantic similarity at different scales, the example words with the largest growth rate at different scales are found, as shown in the figure, it can be seen that: the data comparison effectiveness under the cosine similarity calculation describes the altitude information in a class of coordinate points; the data comparison output under the environment of the Jaccard algorithm solves the road network accessibility information observed by the survey; the perceptual hash algorithm intervenes The data comparison effect under the perceptual hash algorithm intervention reflects the information distribution pattern of water environment and human facilities; the histogram mask data is closely associated with the overall posture of the mountain area; and the survey route recorded by the painter, the subjective emotional expression when drawing, the objective reference constraint, the unconscious interpretation feedback and the recording deviation are also highlighted under the SIFT algorithm environment. In addition, with the model series model obtained through the mapping of the DEM elevation data model, differences in the metrics in the same region of the time-series image records can also be seen, indicating that the semantic similarity of the spatial feature pose is considered, and spatial information beyond the semantic similarity of the text is mined.

After identifying the preferred implementations in hybrid image resources and obtaining extremely strong implicit relationship mining capabilities, additional changes and modifications can be made to these implementation cases. Obviously, scholars in cross-disciplinary research fields can make various changes and variations to this method implementation case, and the paradigm innovation of this study intends to promote more research changes and logical reuse to obtain more discoveries.

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