Mountain Top Algorithm: Complex Historical-Geographic Network Data Analysis based on Structure, Dynamics, and Function

Ziyang Weng* , Yidan Hu, Shuhao Wang, Wenhui Wang, and Yuhao Liu
School of Information Management, Wuhan University, Wuhan
weng_ziyang@whu.edu.cn, Hydan1109@whu.edu.cn, wangshuhao@whu.edu.cn,
wangwenhui@whu.du.cn, 2019301040050@whu.edu.cn
*corresponding author

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***Abstract*—This paper constructs a social knowledge/genetic algorithm model based on a mathematical approach that always relates the behavior time, behavior distance, and geo-data acquisition quality of all mobility patterns to the overall geographic knowledge evolution process. In order to address the existence of multiple interactions in complex data systems in the social computing domain, such as transportation networks (mountain, geography, and accessibility) under different geo-constraints, including interaction and survival needs in socio-ecological networks, including agro-genetic, demographic, and economic interaction networks, we realize how to find the peaks in the data network, i.e., the few "nuclei" with high connectivity, in the data organization process. The model can be used to identify the nuclei of high connectivity in the data network, and the key role of the nuclei in the effective derivation of social computing, and to algorithmically describe the above behavior. The model can be used both to discover the causes of in situ behavior at the macro level and to provide new solutions for modeling coupled object-event-process data in complex social computing.**

Keywords-component; Mountain top algorithms; complex networks; dynamics; geosciences

I. Introduction

Mountain top algorithm (MTA) is an optimization of swarm intelligence algorithm, which simulates the behavior of human exploring unknown environment in a mountain range, and analyzing the overall mountain structure by setting coordinates, and choosing the best route to reach the peak of the mountain range. The research logic is derived from the "Six Methods of Cartography", taking the spatial observation of mountains as an example, focusing on the methods of exploring the object mountains and ranges in early societies and the recording process of effectively discovering, comparing, and finally acquiring the peak information, as well as the computational evaluation of the geo-image data products produced and stored in East Asia at a later stage. The process of recording, enhancing, absorbing, and optimizing the geo-geographic information recording process.

By describing the existence of group wisdom in a complex multi-layer network organization, MTA algorithm effectively identifies the goal-driven value "nucleus" (i.e., peak) in a complex historical-geographical network environment, and uses it as a node to analyze aggregated information and realize an optimized strategy. The second part of the article introduces the concept of summit and the historical background of mountain exploration; the third part focuses on the core element of the model construction, the summit, which has both natural and special properties through aggregation with multivariate data; the fourth part provides an abstract overview of the structural features of the complex historical-geographical network; the fifth part introduces the principle, calculation method and process of MTA; the sixth part introduces the principle of MTA. The sixth part is based on the calculation of graph data and presents a case study on the acquisition of peak data in the 10th-16th century graphs; the last part concludes and outlooks this study.

II. Background

The current research on complex networks in social computing still focuses on single networks (single-layer networks), ignoring the existence of multiple network interactions in real complex systems. For example, (mountain, geographic environment and accessibility) transportation networks under different geo-constraints in civilizational evolutionary computation, interactive and survival needs in socio-ecological networks, interaction networks of agricultural genetics, population metabolism, and economy, etc. In view of the fact that single-layer networks can no longer meet the requirements of complex systems in practical historical and geographic country studies, this paper tries to introduce "Network of networks", "Multiplex network" and "Interdependence network". This paper attempts to introduce the concepts of "Network of networks", "Multiplex network" and "Interdependent networks" to summarize the algorithmic models and the frontier directions of social computing.

In modern society, there are a large number of complex systems formed by the accumulation of data acquired and recorded by collectors, such as Internet, communication networks, power networks, biological neural networks, metabolic networks, scientific research cooperation networks, social cooperation networks, social relationship networks, etc. On the contrary, in the field of social computing, researchers can obtain part of computable, complementary, and transformable information resources based on the accumulation of documentary information, in situ examination, and associated research archives in the historical process, which can be transformed into complex social evolutionary networks after data extraction, data mining, and data complementation, which have striking similarities with the present-day digital network ecology [1].

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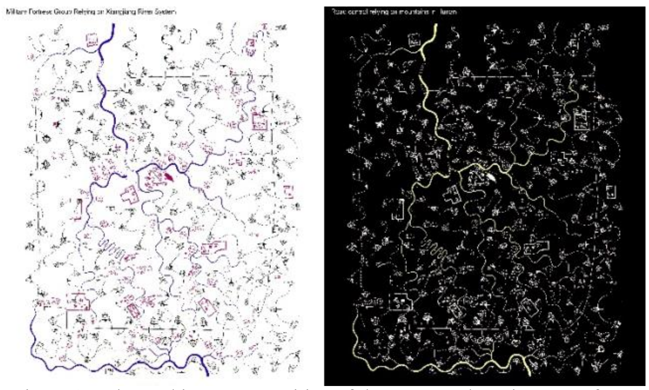

Figure 1. Enhanced image recognition of the excavated garrison map from Han tomb No. 3 in Mawangdui

At the end of the 20th century, Barabasi et al. discovered a power-law distribution reflecting the actual network, and through an empirical study of the World Wide Web, revealed that its essence is composed of a small number of highly connected pages strung together, with more than 80% of pages having less than 4 links. At the end of the 20th century, the introduction of the microworld and scale-free network models broke the conventional thinking of using random graphs to describe complex networks in reality, thus establishing a landmark in the study of complex networks [3].

Similarly, when looking back at historical societies, the search for discovering the peaks standing in the data network, i.e., the few highly connected nuclei, becomes the key to effective extrapolation of social computing.

III. Focus on: Peaks in Complex Historical and Geographical Networks

In solving real-world social computing problems, the usual algorithm reuse is prone to the problem of reading the computational results due to uneven data quality and insufficient data variety. In this case, experts in sociology, history, and anthropology need to be brought in to discuss the "non-computational evidence" of computational results. It is worth noting that in the face of the disappearing historical scenes, it is necessary to find the "interconnected" relationships in order to build an algorithmic model based on data resources and data logic.

In this paper, we propose the additional qualifier "non-computational evidence", which refers to the change of events after some implicit influence, especially the multiple heterogeneous influences in a single event. It is used to explain unexplained phenomena. As a result, much of the literature on climate impacts and climate change is unable to confirm the extent of perturbations in the archaeological record or to directly synchronize the occurrence of social events with climatic events, despite their possible presence in the archaeological record [4]. However, where researchers are able to demonstrate causality in advance with event-calculated evidence, climate factors can only be safely identified when multiple independent parameters agree on the same thing, and we can safely determine the true climate "effect" or "change". Since most complex systems require data nodes that have multiple functions, can be interconnected, and can describe the role of relationships between them, the multiple functions are qualitatively distinct and cannot be superimposed to constitute the data available for the computational process of a multi-layer network. To summarize, complex historical and geographic network data have the following main characteristics:

A. Massive network data

The total amount of historical and geographic network data is much smaller than modern network data, which can be effectively enriched by complementing and extrapolating to meet the computational needs. The scale of real network data is usually very large, with the number of nodes generally ranging from tens of thousands or hundreds of thousands to hundreds of millions or billions, so the study of such a "massive" network of nodes requires the search for better algorithms and models to portray them, and the research results and research trends are highly reusable for the study of historical and geographical network data.

B. Sparsity

The sparsity of historical and geographic network data is reflected in the fact that the connections between the data are kind of missing items, the temporal order is incomplete, and the reliability of the records needs to be checked. Due to the level of historical development, the sparsity between the record data must be realized by the intervention of algorithms. Statistics tell us that the number of edges of most real networks is approximately of linear order of the number of nodes N, i.e., of order O(N), such as networks of tens of thousands of nodes, whose edges are typically in the hundreds of thousands or millions, unlike fully connected networks which are of order 2 of N.

C. Micro World Features

Small-world networks are typically characterized by short average paths and large clustering coefficients. Six degrees of separation theory is such that any two people in the world can be directly linked on average by just six relationships. While in the historical geographic network, the historical data is more sparse historical geographic network data between the path length is shorter, concentrated in several different concepts of individuals, groups, and classes. In the data pre-processing stage should pay attention to the labeling of relationships, the management of labels and the involvement of computation.

D. Power-law distribution of nodal degrees

The degree distribution of a network is the distribution of the number of nodes with different percentages of edges, that is, the probability that the degree of a node in a randomly selected network is k. The degree distribution of a nearest neighbor network, such as a ring, is a δ "peak" function because the degree of each node is 2. The degree distribution of a completely random network is closer to the Poisson distribution, i.e., the degrees of the network nodes are mostly around a mean, and the degrees away from the mean are almost nonexistent. The concept of "peak and group of peaks and mountains" defined in this paper refers to the core motive, auxiliary motive and specific development law, which can provide a new analysis path for historical and geographic social computation.

IV. Research bottlenecks in complex historical and geographic networks

Historical boundary changes, geological and geomorphological traces, and intergenerational social documentation together constitute the basic formation process of data on the complex network of history and land, and most of the existing studies have analyzed the mechanism of their records independently. However, in practice, the close correlation and interaction between historical territory data and geological and geomorphological traces are richer than human archives. A large number of studies have been conducted in the past to reconstruct zoning models, construct road network databases, and carry out geographic analysis and network analysis through historical documents [5]. However, the correlation analysis of natural science data and historical human events is still insufficient. For example, large-scale climate change is distributed in multiple types of records of hydrological features, plant migrations and geological mechanisms, especially at the beginning of climate change, and the climate information recorded in individual archives cannot be timely discovered and archived in time due to the conditions of social processes, which greatly inhibits the reliability and comprehensiveness of records.

In the case of climate, for example, when a single dynamic disturbance data network of climate ontology constitutes a network of interactions with social governance and community survival, individual people and individual social forms become individuals in a two-layer network. This two-layer network exhibits extremely complex dynamical effects. Whether people's perceptions of climate are conducive to reducing social risk perceptions greatly affects the likelihood of major historical events, for example, if the power hierarchy, based on the "peak", suggests that there is a risk of a certain climate persisting, the top-down governance behavior will trigger policy adjustments, thus drawing the attention of society as a whole and achieving risk prevention In this way, we can prevent and control the spread of disasters caused by climate change. On the contrary, if we ignore or disregard the characteristics of climate change and wait for the bottom-up information feedback to be aggregated into events, we will find that the outbreak of climate disasters will trigger the outbreak of crisis in social governance, and the propagation of crisis will increase the outbreak threshold of disaster impacts, thus causing comprehensive governance chaos, impeding social progress, and even triggering regression [6]. At present, historical archival information-event analysis coupled with network and socio-natural resource national systems has become a new research direction, which helps to further reveal the influence mechanism of group, economic and social factors in the evolution of civilization and provides theoretical guidance for social computing-services control.

Similarly, facing the demand for effective coordinated response of complex historical-terrestrial network systems requires the entire underlying network to provide vital disconnected space of land, energy, water, transportation, communication, military, and fiscal supply data, which are closely dependent on each other, together with the cooperation of government structures, governance ecology, and other relationship markers to reflect the multi-level complex structure. The data have complex relationships with multiple connections, feedback and feedforward paths, and various branching topologies. The reliable operation of the algorithmic model must rely on a computer control system, a data acquisition and control system, to ensure that the entire complex system operates safely and efficiently. The typical "system of systems" is limited to the study of single-layer networks is far from meeting the needs of reality, and we need to change the current situation of the relative lack of theory, methods and technical means in multilayer networks.

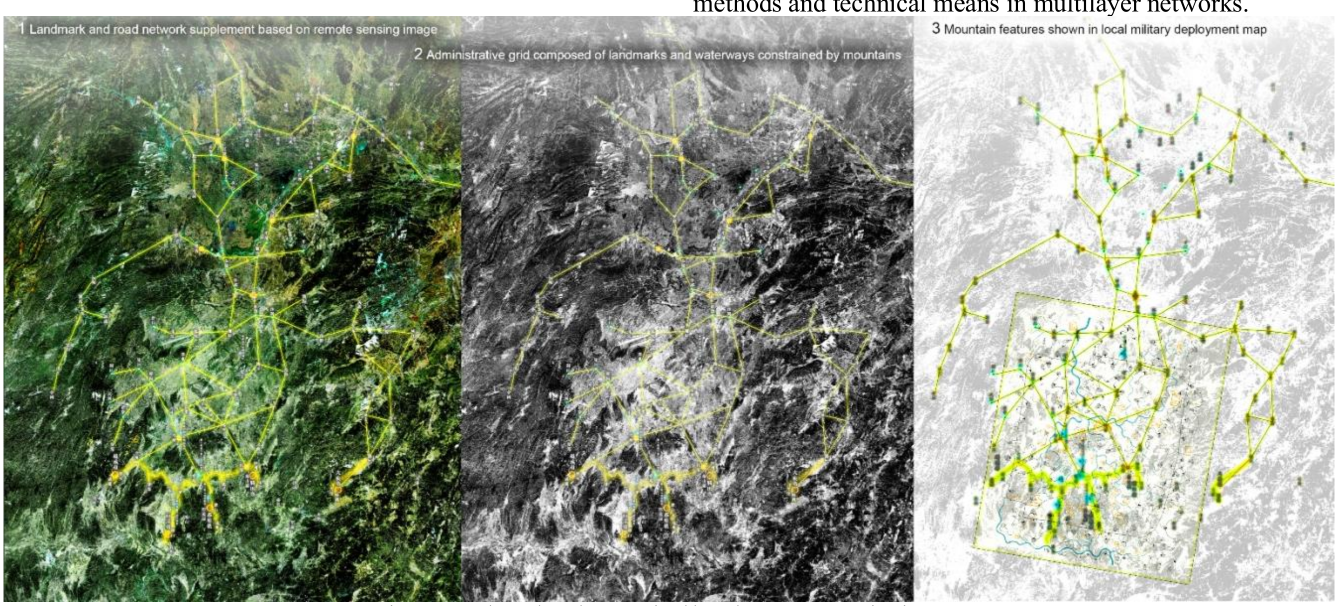

Figure 2. Peaks and roads recognized based on remote sensing images

What are the characteristics of multilayer networks in terms of structure, dynamics, vulnerability and robustness, and what are the more complex phenomena than single-layer networks? This research team constructs a topological platform of Chinese categorical remote sensing image data based on GIS environment, integrates a large amount of effective historical administrative divisions and hydrological road network information, constructs a knowledge map by associating information with specific historical events, and implants mapping with spatio-temporal labels to complete the construction of multi-layer network structure and data organization.

V. Historical Geographic Network Features

A. *Structure of multi-layer networks*

As shown in the figure, the number of nodes in each layer is the same, but each layer has different topologies. The connected edges can be directed or undirected, weighted or unweighted, while the inter-layer connections are channels to communicate different layers, which can also be directed or undirected, weighted or unweighted. Therefore, when the intra-layer connection and inter-layer connection relationships are given, the structure of the multilayer network can be basically determined.

The structure of the network (i.e., the interactions between the nodes of the network) is completely determined by the Laplace matrix corresponding to the network. In the unweighted network, if the jth node is connected to the i-th node, the element of the j-th column of the matrix is -1, otherwise it is 0; and the sum of the elements of each row of the matrix is 0. Based on this, the network structure and the matrix can be realized in correspondence, and the mathematical law provided by the Laplace matrix, the network Laplace matrix, can be used to determine the network structure. law, the eigenvalues of the network Laplace matrix, are able to reflect certain important dynamics (such as propagation, synchronization, etc.) properties of the network.

How to consider a multiple network with M layers and N nodes per layer? Assume that the inter-layer connections are identical and that there is no directional full connection without self-loop. We can call the whole multi-network Laplacian matrix a super Laplacian matrix, which can be decomposed into intra-layer and inter-layer parts, where the intra-layer matrix is the direct sum of the matrices of the layers and the inter-layer super Laplacian matrix is the tensor product of the inter-layer matrix and the unit matrix, equal to the N-fold of the spectrum of the inter-layer Laplacian matrix. The spectrum of the interlayer Laplacian matrix is also the eigenvalue of the entire multilayer network super Laplacian matrix. These are the most basic relationships for analyzing the structural and spectral properties of multilayer networks. These eigenvalues are generally not easy to obtain analytic expressions, but for several special cases it is possible to obtain analytic expressions.

B. *Degree distribution of multi-layer networks*

The degree distribution of a network is important for the network. So how to portray the degree distribution of a multilayer network? For example, both layers are SF networks (or random ER networks, micro-world networks), or the two layers are different networks, and the inter-layer connections can be degree positive correlation connections (the two layers are interconnected with degree large and degree large nodes), degree negative correlation connections (the two layers are interconnected with degree large and degree small nodes), or random connections, as the figure shows random, positive and negative correlation connections.

The most common connection in practical problems is positive correlation, for example, in interpersonal-social structure-event networks, often the set of relationships of people with more social resource relationships is also larger, and the influence on events is also larger. The study of this problem requires methods such as multivariate random variables and their distributions in probability statistics, joint distribution functions and marginal distribution functions.

C. *Peaks on multi-layer networks*

Social events in multi-temporal space also show the same characteristics, where diffusion and synchronization last longer and have deeper impact, and the explicit differences are rapidly revealed after the discovery of implicit relationships with dynamic diffusion and genetic synchronization patterns.

The important task of studying synchronization is to determine its synchronization domain, which can be divided into four cases: unbounded, bounded, multi-region, or disrupted synchronization. To measure the synchronization capability of the network, the minimum non-zero eigenvalue of the Laplace matrix of the network and the ratio of maximum eigenvalue to minimum non-zero eigenvalue, R, are generally used.

First, we observe the simplest two-layer structure, where the same star-shaped network is connected by an edge between layers, and there are three cases: center node connected to center node, edge node connected to edge node, and edge node connected to center node. Studies have shown that degree large node to degree large node connections have stronger synchronization capabilities. It is also easy to understand that for two systems to work together (synchronization), the interconnection of the most important members of each system is the most critical.

For the more complex multilayer scale-free network, the synchronization ability of the multilayer network is proportional to the interlayer strength when the interlayer strength is relatively small, and the time scale of the diffusion dynamics becomes smaller and smaller in inverse proportion to the interlayer strength, indicating that the diffusion becomes easy; and with the further increase of the interlayer strength, the improvement of the synchronization ability becomes slow, and the time scale of diffusion is not too small.

The minimum non-zero eigenvalue of the multilayer network is significantly larger than that of the single-layer network after the interlayer strength is appropriately large, indicating that the synchronization capability of the multilayer network is much larger than that of the single-layer network. For the case where the synchronization domain is bounded, either too large or too small interlayer strength of the network is not conducive to the synchronization of the multilayer network, i.e., there is an appropriate optimal coupling strength to maximize the synchronization capability of the multilayer network.

For multilayer networks coupled with networks of different nature, many new complex phenomena arise from their synchronization properties. In the study of a two-layer network coupled with a one-dimensional network (each node is connected to only four neighbors on the left and right) and a WS micro-world network (with a small number of "long-range" edges), where the average degree is set for two single-layer networks, the intra-layer coupling strength of the one-dimensional network is assumed to be J1, the intra-layer coupling strength of the WS world network is J2, and the inter-layer strength is J. Using Kuramoto's same step model to study the effects of J1, J2 and J on the whole two-layer network by mean field analysis, it can be found that when the weak coupling J1<<1 of the one-dimensional network, the increase of J inhibits the synchronization of the whole network instead, which is due to the asynchrony of the one-dimensional network hinders the synchronization of the WS micro-world network. In contrast, when the intra-layer coupling strength J1 of the one-dimensional network increases to a large enough extent, it makes J increase to promote the synchronization of the WS micro-world network, thus improving the synchronization of the entire two-layer network. These findings can explain many complex historical events and social phenomena.

D. *Robustness and vulnerability of multi-layer networks*

Realistic networks exhibit robustness to random attacks (it is difficult to hit Hubs nodes since they are random) and vulnerability to deliberate attacks (a deliberate attack can easily bring down a network because of the presence of Hubs nodes) due to the extremely heterogeneous degree distribution and the presence of Hubs nodes, which are extremely important characteristics of complex networks. This is an extremely important characteristic of complex networks. For multilayer networks serving social computing, this robustness and vulnerability is even more evident when the event records are artificially altered and re-recorded, resulting in the possibility that the data itself is a virus, the wrong node makes the logical chain break, and the phenomenon of network cascade failure occurs, which is also the effect of the data resources themselves being stored in an inter-layer coupled association. The so-called cascading failure phenomenon is when the failure occurs in the first layer of the network, it will lead to the failure of other layers of the network nodes, which in turn further damage the first layer of the network, leading to catastrophic consequences.

VI. Mountain top algorithm

A. *Principle*

In order to find the highest point of a group of mountains, the starting point of a mountain entry path is usually chosen arbitrarily as the starting point for local climbing (i.e., climbing to the highest point of the mountain), and after reaching the highest point of the mountain (local highest point), this is used as the base point to search for higher summits, and the higher summit point is used as the target point to start the next round of local climbing until the summit.

Several summit points of the base point are selected as candidates for "higher points": reference points near the base point can be selected densely, and reference points far from the base point are sparse because they are not reached. If the peak is above the horizontal line of sight, the peak is considered to be higher than the base point.

This algorithm is an intelligent algorithm for solving global optimization problems using the common knowledge of survey techniques to determine the highest point of a group of mountains. The algorithm consists of a management mechanism (mainly responsible for algorithm process control and coordination), a target generation strategy (responsible for generating peak points), and a local problem construction and solving mechanism. The basic process of solving the global optimization problem is as follows.

1) Determination of the base point by the management mechanism
2) Peak points of the base points are generated by the goal generation strategy.
3) Selection of peak vertices by the management mechanism according to certain criteria.
4) Construct local problems for all the selected peak vertices and solve these local problems using a local search algorithm.
5) After obtaining the solutions of all the selected local problems, the management mechanism determines the next base point and performs a new round of iterations until the algorithm termination condition appears and the current best feasible solution is used as the solution of the problem.

B. *Mathematical description*

1) Description of the global optimization problem

Consider global optimization issues：

$$\begin{cases} \min F(x) \quad X \in \mathbf{R} \subset E^n \\ \mathbf{R} = \{X \mid g_i(X) \geq 0, \quad i = 1,2,\cdots,m\} \end{cases} \tag{1}$$

$$G(X) = \left(g_1(X), g_2(X), \cdots, g_m(X)\right)^{\mathrm{T}} \tag{2}$$

The local optimization algorithm is an iteration-based method for solving optimization problems, which has the inherent property that the iteration points generated by the optimization process must be within the single-peaked region where the initial points are located.

2) Peak point generation strategy

Based on the idea that the peak vertices can be selected densely near the base point, while the peak vertices can be obtained more sparsely at a place far from the base point, various target generation strategies can be designed.

As the base point $X^B = (x_1^B, x_2^B, \cdots, x_n^B)^T$, we will discuss the square peak generation strategy and the spherical peak generation strategy to generate the first order peak at the base point.

a) *Square Peak Point Generation Strategy:*

The cube peak generation strategy is to select the $k(k=0,1,2,\cdots)$ order peak of X^B in the $intersection$ of the n-dimensional cube surface with prism length $2r_k$ centered at x and the feasible domain R, where it is a function of h、k、X^B、F、G, a predetermined constant$h(>0)$ (called the basic peak step), and $r_0=0<r_1<r_2<\cdots$; when $k=0$, $X^B$is the only peak point.

The geometric significance of the kth order peak vertices generated by the square peak vertices generation strategy is illustrated with n as an example. As shown in the figure, the first-order peak vertices are taken from the

$$\left\{(x_1^B \pm r_i, x_2^B \pm r_k)^{\mathrm{T}}, \left(x_1^B \pm r_k, x_2^B \pm r_j\right)^{\mathrm{T}} \mid i=0,1,2,\cdots,k;\ j=0,1,2,\cdots,k-1\right\} \cap \mathrm{R} \quad (3)$$

he construction of r_k mainly considers the case where r_k is a h、k function, which can be determined by the isometric method, arithmetic increasing distance method, Fibonacci increasing distance method, and geometric increasing distance method.

b) *Spherical peak generation strategy:*

The spherical peak point generation strategy is the first order peak point in the intersection of the dimensional sphere.

$$(x_1-x_1^B)^2+(x_2-x_2^B)^2+\cdots+(x_n-x_n^B)^2=r_k^2 \qquad (4)$$

The peak point X^B of the $k(k=0,1,2,\cdots)$ order is selected from the intersection of the feasible domain$R$ and the spherical spherer_k, which is exactly the same as that of the square peak point generation strategy. Because of $r_0=0<r_1<r_2<\cdots$, under the spherical peak generation strategy, the peaks of the same order are equally distant from each other, and the peaks of higher order are farther away from X^B.

Take $n=2$as an example, we illustrate the geometric significance of the kth order peaks generated by the spherical peak generation strategy. If it is desired to take at most q kth-order peak, it is worthwhile to select X^Bpoints among the intersections of the starting rays (q rays are generally uniformly distributed) with the circumference of the circle $(x_1-x_1^B)^2+(x_2-x_2^B)^2=r_k^2$ as peak points, as shown in the figure, here$q=q(h,k,X^B,F,G)$. Similar to Algorithm 2 (see section), an algorithm for generating peak points by spherical peak point generation strategy can be obtained.

C. Construction of Local Problems and Local Optimization Seeking Algorithms

The Mountain top algorithm is proposed to solve the global optimization problem whose objective function is a multi-peaked function, firstly, divide R into two disjoint single-peaked regions (or divide R into two disjoint single-peaked regions, and make each single-peaked region as large as possible), each single-peaked region corresponds to a local problem, so that the global optimization problem is decomposed into a series of sub-problems whose objective function is a single-peaked function (local This decomposes the global optimization problem into a series of sub-problems (local problems) whose objective function is a single-peaked function; secondly, the solution of the local problem is obtained by the method of solving the optimization problem whose objective function is a single-peaked function; finally, the solution of the global optimization problem can be obtained by simply comparing the solutions of the local problems.

D. The memory mechanism of the peak algorithm

In order to avoid repeated search in the searched region and improve the convergence speed of the algorithm, a 3-level memory mechanism of the peak algorithm is introduced: base point memory in the first level; peak point memory in the second level; and local merit-seeking memory in the third level.

1) Baseline Memory

Base point memory $MB=\varnothing$ remembers all base points. Initially; if X^B is base point, then$MB=MB\cup\{X^B\}$. If base point memory is implemented, the condition corresponding to fragment 3 of Algorithm 1 is changed to: if $F(LocalX^{min}\le F(X^{min}))$ and Local $X^{min}\notin MB$. In this way, it is possible to avoid repeating a point as a base point during the iteration.

2) Peak point memory

Peak point memory (MO) remembers all the peak vertices that have constructed a local problem and implemented a local search. Initially $MO=\varnothing$; if X^O is a peak vertex of some base point and solves the local problem atX^O, then if peak vertex memory is introduced, the condition corresponding to fragment 1 of Algorithm 1 is changed to: if $F(X^O)\le F(X^B)$and$X'\in MO$ not exist to make$\|X'-X^0\|\le\varepsilon,\varepsilon>0$ for a predetermined accuracy). In this way, the local problem can be constructed at most once for any point and its neighborhood.

3) Local merit-seeking memory

The local merit search memory (ML) remembers some of the iteration points experienced by the local merit search process. Initially $ML=\varnothing$; if X^L is an iteration point obtained by the local search process, and $X'\in ML$ can't satisfy $\|X'-X^L\|\le\varepsilon(\varepsilon\ge 0)$ the predetermined accuracy), then$ML=ML\cup\{X^L\}$; otherwise, this local search is terminated, because if it is smooth and does not have mutability, the quality of the obtained iteration point is generally not substantially better than the previous one if the local search is continued. In addition, the condition corresponding to fragment 1 of Algorithm 1 can also be changed to$F(X^O)\le F(X^B)$: and there is no $X'\in ML$make for $\|X'-X^0\|\le\varepsilon(\varepsilon\ge 0)$a predetermined accuracy) when there is a local search for memory.

MB、MO、ML embody the 3 levels of memory of the peak algorithm, it is clear that there are $MB \subseteq ML$、$MO \subseteq ML$, choose one or more of these memories as needed. In order to achieve a fast lookup of the elements in MB、MO、ML (e.g., dichotomous lookup), their elements should be sorted simultaneously during the iteration (e.g., dichotomous interpolation sort.

VII. Cases and Findings

Previous studies have realized spatio-temporal data transformation based on literature, codices, maps, communications, publications, and air and space data [8]. Based on the assignment of values to spatio-temporal trajectories, data mining, data complementation, and algorithmic constraints, a GIS synchronization network involving geo-data acquisition [9] and geo-knowledge product production in continuous time periods was formed. The experiments show that we are able to form effective algorithms from dynamic data and computational inference, and that the algorithms are effective and can help to improve the efficiency, objectivity and reliability of the analysis by automatically evaluating the distinction and linkage between genotypes and phenotypes generated through the data in the process of capturing the evolutionary behavior and cognitive characteristics of civilizations, which helps to reduce computational invalidation, interruption of inference, reduction of inference errors and reduction of experimental costs.

The model developed by this algorithm shows that there is a positive nonlinear relationship between the extensive geo-data value peak area and the human exploration area exploration. Current research shows that clearly identifying and defining the driving goals, relational factors, and interactions of group behavior is effective in describing and explaining group intelligence in terms of cooperative mechanisms. However, to gain analytical insight in the high-dimensional phase space, relying only on specific regional scenes, non-wide ecological events; or relying on object changes to generalize scene characteristics, non-dependent process fluctuation frequency and other analytical results, in which episodic behavior is difficult to automatically converge into a convincing understanding, still need continuous simulation-based extrapolation of experiments to effectively achieve the maximum synergistic effect of service deep learning.It is gratifying to note that the occasional emergent variant data in the computation, with feedback from domain experts, clearly meet the initial design goals. Research breakthroughs that cannot be directly identified or evaluated in social science field research can be found to be convincingly understood when combined with the complement of broader domain knowledge.

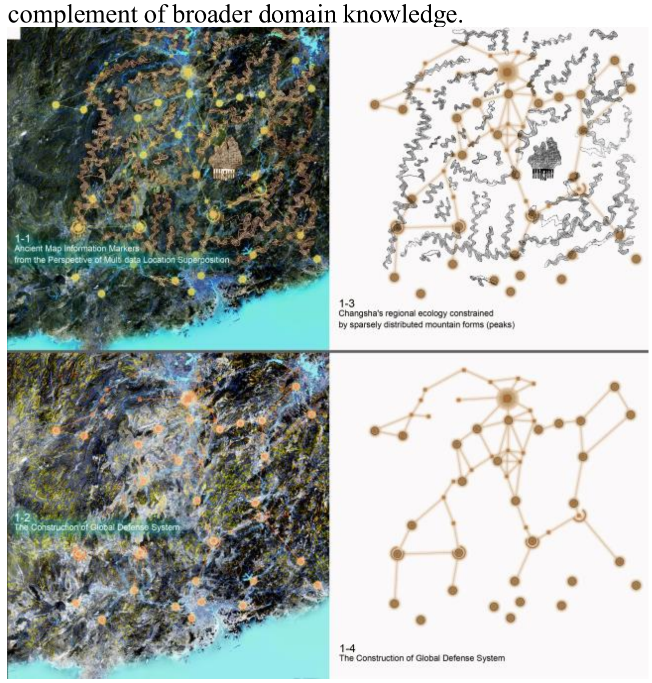

Figure 3. Graph scenario space decoding and structure extraction

Start & Finish	Land/Water	Distnace	Terrain Complexity	Pedestrim Speed	Military Speed	Road Accessibility	Start & Finish	Land/Water	Distnace	Terrain Complexity	Pedestrian Speed	Military Speed	Road Accessibility
changsha-liuyang	L	164.64	1.4	20	30	2.60	qiyang-xintian	L	180.00	1.2	40	60	11.11
changsha-xiangyin	L/W	108.48	0.4	60	120	331.86	qiyang-changning	L	138.96	1.2	40	60	14.39
changsha-ningxiang	L/W	89.28	0.4	60	120	403.23	changning-xintian	L	148.56	1.2	40	60	13.46
changsha-xiangtan	L/W	108.24	0.4	60	120	332.59	changning-guiyang	L	197.76	1.2	40	60	10.11
ningxiang-yiyang	L	95.76	1.2	40	60	20.89	yongzhou-dongan	L	71.28	1.2	40	60	28.06
yiyang-hanshou	L	126.24	1.2	40	60	15.84	yongzhou-daozhou	L	245.28	1.2	40	60	8.15
hanshou-changde	L/W	77.04	0.6	50	100	216.34	daozhou-yongming	L/W	89.28	0.6	50	100	186.68
changde-taoyuan	L/W	63.36	0.6	50	100	263.05	daozhou-jianghua	L/W	77.52	0.6	50	100	215.00
xiangtan-xiangxiang	L/W	101.04	0.6	50	100	164.95	daozhou-ningyuan	L/W	88.08	0.6	50	100	189.22
xiangtan-liling	L/W	144.00	0.6	50	100	115.74	yongming-jianghua	L/W	70.56	0.6	50	100	236.21
liling-pingxiang	L/W	84.24	0.6	50	75	148.39	xintian-guiyang	L	142.80	1.2	40	60	14.01
liling-youxian	L	177.36	1	40	60	13.53	xintian-jiahe	L	89.52	1.2	40	60	22.34
xiangtan-youxian	L	248.64	1	40	60	9.65	jiahe-lanshan	L	70.32	1.2	40	60	28.44
xiangtan-hengzhou	L/W	266.40	0.8	50	100	46.92	lanshan-ningyuan	L	71.52	1.2	40	60	27.96
hengzhou-qiyang	L/W	200.16	0.8	50	100	62.45	lanshan-linwu	L	101.52	1.2	40	60	19.70
hengzhou-changning	L/W	139.20	0.8	50	100	89.80	guiyang-chenzhou	L	66.00	1.2	40	60	30.30
hengzhou-leiyang	L/W	146.40	0.8	50	100	85.38	chenzhou-yongxing	L	87.84	1.2	40	60	22.77
hengzhou-anren	L	173.76	1	40	60	13.81	chenzhou-zixin	L/W	71.28	0.6	50	100	233.82
youxian-chaling	L	75.60	1	40	60	31.75	chenzhou-yizhang	L	104.40	1.2	40	60	38.31
anren-chaling	L	67.68	1	40	60	35.46	yizhang-lechang	L	129.60	1.2	40	60	15.43
anren-leiyang	L	116.40	1	40	60	20.62	yizhang-rucheng	L	186.72	1.2	40	60	10.71
anren-lingxian	L	139.92	1	40	60	17.15	zixin-youxian	L	53.04	1.2	40	60	37.71
anren-yongxing	L	83.28	1	40	60	28.82	zixin-guidong	L/W	168.00	0.6	50	100	99.21
qiyang-yongzhou	L/W	65.28	0.8	50	100	191.48	zixin-rucheng	L	156.96	1.2	40	60	12.74
qiyang-ningyuan	L/W	252.96	0.8	50	100	49.41	lechang-qujiang	L	113.04	1.2	40	60	17.69

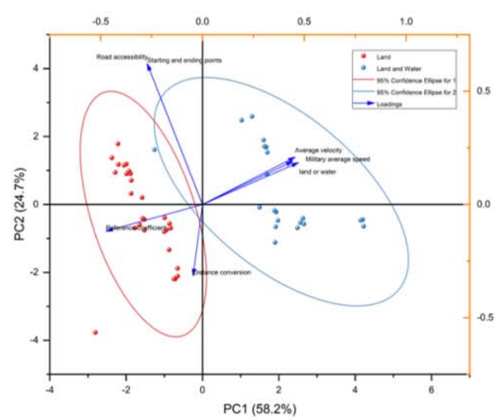

Figure 4. Data Derivation and Analysis of Mawangdui Silk Map

VIII. Future Work

By targeting some exploration of multilayer networks in social computing, the data organization and computational analysis of complex historical and geographic networks based on structure, dynamics and function, according to the research idea, the above algorithms can be modified at a later stage. For example, the local Newton method is a local optimization-seeking algorithm obtained by adding special treatment of boundaries and inflection points, etc. to the Newton method, and the local DFP method [10] is a local optimization-seeking algorithm obtained by adding special treatment of boundaries, etc. to the DFP method.

It can be found that the peak algorithm can achieve the discovery of core problems in the complexity of multi-layer networks compared with single-layer networks, and is a more ideal algorithmic model for studying complex network systems in history and geography, especially in multi-layer ER small-world networks[11] and multi-layer SF scale-free networks can be applied to find the trajectory of the event process more closely and guide the discovery closer to the true historical nature, and also for exploring the large-scale social evolutionary dynamics evolutionary mechanisms and reshaping socio-ecological topologies, by providing new perspectives and methods.

We derive a simple model based on the search for civilizational evolutionary value goals that allows us to gain insight into the heterogeneity of goals in socio-ecological diversification: understanding the complexity of goals. The algorithms presented in this paper are not intended to apply to one-issue scenarios, but rather to provide ideas for better capturing more detailed behavior in future work.

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