Nautical Chart Algorithms: A Feedback Strategy to Consider Knowledge Data Production Behavior

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***Abstract*—Nautical chart algorithm (Nautical chart algorithm) is a new meta-heuristic swarm intelligence algorithm based on the ant-lion algorithm, taking into account the whole process of geo-data acquisition, distribution processing and integration release in the nautical charting process in the era of great navigation, by constraining the behavior of voyage ships exploring geo-data, the data acquisition conditions and expansion laws in ports, the attraction of data exchange and sharing social mechanisms, the establishment of data specification standards and the process of common knowledge evolution. The proposed algorithm can achieve significant improvement in the ability of global sensing and local event deduction for early geo-knowledge production with fast convergence, strong global search capability and high solution accuracy by testing the test function.**

Keywords- nautical chart algorithm; intelligent evolution; social computing; group intelligence

I. Introduction

To address the shortcomings of the core ALO algorithm in terms of low convergence accuracy and the tendency to fall into local optimum solutions, this paper proposes a dual feedback mechanism that introduces the characteristics of fleet-port capacity and rule improvement rate as dual feedback information into the algorithm, realizes the import of rule improvement elite variation strategy, and realizes an evidence-based research paradigm for early global geopolitical knowledge production. A dynamic adaptive feedback adjustment strategy is used to improve the convergence accuracy by dynamically adjusting the port attractiveness size; a diversity feedback Gaussian variation strategy is used to enhance the diversity of fleet exploration behaviors and avoid premature maturity of the algorithm.

Evolutionary algorithm that consider the behavior of knowledge data production. Nautical charts are geo-knowledge data products that are rapidly iterating along with the great discovery of navigation and are high-quality cases for analyzing and studying knowledge data production in the process of social evolution. In this paper, we propose a basic model for establishing a nautical chart algorithm, based on the above-mentioned nautical chart mapping behavior in which the geo-location data of ship exploration is acquired by distributed information collection nodes to realize the mathematical decoding of the behavior of geo-co-knowledge evolution.

II. Motivation

Optimization of algorithm based on multi-objective tracking: The ant-lion algorithm was proposed by Seyedali Mirjalili in 2015 [1], drawing inspiration from the random wandering of ants in nature, the construction of traps by antlions, trapping ants into traps, capturing ants and reconfiguring traps. It has been applied abroad in the fields of pole system structure optimization [2], useless power distribution problems [3], community mining in complex networks [4]and route planning problems of UAVs [5]. In China, Shijie Zhao et al. introduced the chaos detection mechanism to optimize the SVM parameters[6], and Dongwen Cui et al. used the ant-lion algorithm to optimize the ENN weights and applied them to flood assessment models [7]. ALO shows good convergence performance and accuracy, avoiding local optimality and robustness, but also has the drawbacks of low convergence accuracy and easy to fall into local optimal solutions.

A. Limitations of ALO algorithm and improvement objectives

With the ALO algorithm to care for the research object, it can only realize the global search through the fleet around the randomly selected collection point to achieve the global search, through the adaptive contraction boundary of the collection point in order to achieve local exploitation, far from accurately describe the behavior characteristics of dynamic objects in the research field, but meet the abstract laws in specific scenarios, therefore, there is the challenge of algorithm migration in this study.

The mechanism that the stronger the collection point is, the greater the attractiveness of the construction is not fully utilized in the ALO algorithm. It makes the local exploitation ability not high and the convergence accuracy not high. The parameter I that adjusts the size of the acquisition point is linearly increasing with the number of iterations. However, the approach is an online adjustment approach, and the mechanism is reactive. Therefore, based on the objective law of social development and biological feedback mechanism, it is necessary to dynamically adjust the acquisition point attraction size by using the ability size of the acquisition point as feedback. At the same time, the direct cause of premature ALO algorithm is that the elite antlion in it is guided by the current best population, which does not maintain the diversity of population evolution, thus making the algorithm fall into local optimal solutions, and this phenomenon is especially

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obvious in the multi-peak function [8]. Therefore, on the basis that breakthrough geo-discovery by individual nautical explorers is a source of geo-knowledge evolutionary diversity, the breakthrough variation success rate can be used as feedback to chaotic variation of elite collection points.

B. Fleet-route-geo data and port-collection-calculation hub

The nautical charts are compulsorily collected by the competent agencies of each sovereign state coordinating the ports of each location, compulsorily collecting the logbooks of the ships at berth, the data pooling, and data processing after geo-discovery. Its production is driven by its unique data-hunting behavior, which is simplified as follows: First, a sovereign nation builds information-gathering nodes (data traps) in each landing area of a known route through capital cities (computational hubs), core ports and island supply points, and colonial ports after geo-discovery. Then, attract or constrain fleet behavior through colony ports or island resupply points, and use customs levy logbooks as data collection rules to wait for the return fleet in the route especially in unknown regions to explore to incentivize or punish the completion of geo-data absorption. Once the data enter the distributed dataset, the alignment of data is completed by the data against knowledge released by the calculation hub, and the data is fed back to the calculation hub through the data along the route, then the elimination of data and the iteration and release of overall geo-knowledge are completed, and the sharing of data with nodes is completed after carried by the subsequent fleet. At the same time segment, data collection, collation, verification, iteration, and release of the same model continue to occur until the geo-data along the coastline is coupled with overseas colonization behavior and the nautical exploration of unknown territory is completed.

In addition, it is important to note that the size of information collection points is positively correlated with the military-economic-political intensity of sovereign states. Usually, the more port nodes, the wider the shoreline area the greater the ship density, the stronger the port construction, the greater the chance of being moored, the higher the efficiency of capturing data, and the wider the number of nautical chart products data, data accuracy, and release area.

Random wandering in fleet route area in this algorithm, random wandering is used for all dimensions of each fleet. The route lendable area constructs collection nodes and fleet berthing in: The upper and lower bound decreases as the number of iterations increases. The stronger the collection point density and intensity (i.e., the smaller the fitness function), the higher the probability that a ship will berth in. The fitness value roulette principle is used to randomly select collection points. In addition, elite collection points (areas subject to national political empowerment focus on exploitation), the best collection points for obtaining so far important unknown location data triggering geo-knowledge, will influence the movement of all vessels during the iteration. Therefore, both lower and upper bounds of the collection point parameters should be considered.

The ship geo-location data and the new collection point strategy is to confirm the occurrence of data migration behavior when the adaptation value of the ship mooring is smaller than the adaptation value of the collection point, and the size of the location value of the new collection point selection is proportional to the collection point data acquisition capability. According to the natural law of "survival of the fittest", the larger the number of successful mutations to the number of unsuccessful ones, the more beneficial to the evolution of the group.

III. Principles and Improvement Goals

A. Improvement objectives for the ACO base algorithm

Feedback strategy considering behavioral analysis： In this paper, drawing on the idea of parameter closed-loop control, the features of collection point capacity and group improvement rate are introduced into the algorithm as dual feedback information, and dynamic adaptive feedback adjustment strategy is applied to consider diversity feedback variation.

1) *Dynamic adaptive feedback adjustment strategy:* The collection point size is not steadily getting larger with iteration, and under the influence of human damage risk and natural disasters, there will be the possibility of solidification, shrinkage, or even phase disappearance and complete destruction after the change of exploration field focus, which requires dynamic response to the collection point capacity that. Therefore, this paper proposes dynamic adaptive adjustment parameters I [8][9]. Closed-loop systems using control theory, According to the 1/5 principle proposed by Reichenberg in his study of the automatic adjustment of parameters for evolutionary computation. In the course of the experiment, the size of the collection capacity will be p = Neat /N(Neat Refers to the number of vessels moored into the fleet before the collection point data iteration) As a feedback quantity， 1/5 As a reference quantity. IAs a control quantity. That is, the control parameters of the algorithm should be dynamically adjusted along with the size of the acquisition point capacity. For Ratio I, three adjustment strategies were identified:

   a) $p>1/5$, It means that the collection point development exceeds the expected value, and the capability impact size should be expanded to improve the global search capability.
   b) $p=1/5$, indicating that the acquisition capability is comparable to the expected value and that the global search and local development capabilities are in balance and do not require adaptation.
   c) $p<1/5$, indicating that the collection point is insufficient and does not reach the expected value, when the global search range is too large and leads to low convergence accuracy, the local development capability should be improved to improve the convergence accuracy that the trap should be further shrunk. The stability interval of the parameters can

be extended to [0.2， 0.3]. Thus, the trap sizing strategy is based on the modified Reichenberg principle.

2) *Population improvement elite mutation strategies*: According to the execution process of the algorithm, it can be seen that at the beginning of the iteration, not many optimal solutions are obtained due to the limited search range of the space by the collection points, but with the increase of the number of iterations, the number of non-dominated solutions obtained rises sharply, and although the dynamic adjustment strategy to expand the trap can accommodate more optimal solutions, there are still some optimal solutions lost. Then the promising search region centered on the elite collection point leads to premature maturity of the algorithm, which induces the overall fleet to berth into local optimal solutions. Variation is the source of diversity; therefore, the elite Gaussian variation strategy is introduced based on the population improvement rate Δ as the feedback feature. Its variation timing principle: The absolute value of the difference between the best individual fitness value obtained in this iteration and the best individual fitness value in the nth previous iteration, and the ratio of the best individual fitness value in this iteration is within the range of the population improvement rate, which means that the population improvement does not reach the expected value, is subjected to Gaussian variation.

IV. NAUTICAL CHART ALGORITHMS

A. The behavior of the fleet in choosing the target port

1) Port j attracts a fleet k sailing from port *i*, which chooses to go to port *j*.

2) port j receives fleet k sailing from port i and obtains geo-data on path *(i, j)*.

3) the greater the number of convoys received by port *j*, the more data it obtains about other ports and the more attractive it is to other convoys

4) Port *j* obtains data on all other ports.

B. Fleet selection of target ports

The fleet selects the target port for this voyage by means of a roulette algorithm. In the process of charting a global route, the probability that a fleet *k* chooses to go to a port *j* is a function of the distance, the amount of geo-data and the attractiveness of the port. Here the probability of a fleet of ships carrying geo-data from a port to a port collection point at the moment of time is set to $P_{ij}^{k}(t)$, defined as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\,\eta_{ij}^{\beta}(t)\,\gamma_{ij}^{\theta}(t)}{\sum\limits_{s \in \text{allowed}_k} \tau_{is}^{\alpha}(t)\,\eta_{is}^{\beta}(t)\,\gamma_{is}^{\theta}(t)} \cdot \rho(t) & j \in \text{allowed}_k \\ 0 & else \end{cases} \tag{1}$$

where, α reflecting the relative importance of the amount of geo-data accumulated by the fleet during the voyage, τ_{ij} is the amount of geo-data associated with the route(i,j) ; β reflecting the relative importance of the distance to the port in route selection, η_{ij} is the inverse of the distance between the port i and the port j; θ reflecting the relative importance of the exploration value of the voyage destination in route selection, $\gamma_{ij}(t)$ is a function of the fitness of the port (collection point) j. A taboo table is set for fleet navigation, which does not allow the fleet to consider ports that have already been visited. $\rho(t)$ is a random function reflecting the current security situation of the fleet, defined as

$$\rho(t) = \begin{cases} 1 & \text{rand} > danger \\ 0 & \text{rand} \le danger \end{cases} \tag{2}$$

where is a random number uniformly distributed over $[0, 1]$ and $danger$ is a pre-determined risk factor that also takes on a value between $[0, 1]$. When the fleet is in danger, $\rho(t)$ takes the value of 0; when the fleet is safe, $\rho(t)$ takes the value of 1.

The fitness functions of the port and fleet can be expressed as

$$Fit\left(X_i^t\right) = \frac{n_{t-1}}{N_{t-1}} \tag{3}$$

where, X_i^t denotes the i th variable of the t th iteration, n_{t-1} is the number of ports captured by this variable in the last iteration, and N_{t-1} denotes the maximum value of the number of ports captured in the last iteration.

C. Random sailing of the fleet

As the direct point of collection of geo-information on shipping fleets, the port has the task of obtaining geo-data and reporting it to the information centre. The motivation for the action is to attract more ships to call, to get more information about the routes as soon as possible and to serve the national regime's task of mapping the global routes.

The fleet moves according to a certain strategy when exploring the route, so a stochastic navigation process is chosen to simulate the movement of the fleet in the feasible domain, which can be mathematically represented as

$$X(t) = \left[0, \text{cumsum}\left(2r(t_1) - 1\right), \text{cumsum}\left(2r(t_2) - 1\right), \ldots, \text{cumsum}\left(2r(t_n) - 1\right)\right] \tag{4}$$

where $X(t)$ is the set of sailing steps of the convoy; cumsum is the computed cumulative sum; n is the maximum number of iterative steps; an $r(t)$ is the movement probability function, defined as

$$r(t) = \begin{cases} 1 & \text{rand} > 0 \\ 0 & \text{rand} \leqslant 0 \end{cases} \tag{5}$$

The basic ant-lion algorithm sets rand as a function of uniform distribution on $[0, 1]$ to model the random wandering probability of ants.

To ensure that the fleet strategy wanders within the feasible domain, the fleet navigation is also normalised according to the following equation as

$$X_k^t=\frac{\left(X_k^t-a_k\right)\times\left(d_k-c_k^t\right)}{\left(d_k^t-a_k\right)}+c_k \tag{6}$$

where X_k^t is the normalised position of the fleet k in the t generation; a_k is the minimum value of the fleet navigation strategy; d_k is the maximum value of the fleet k navigation strategy; c_k^t is the minimum value of the k th variable in the t th generation; d_k^t is the maximum value of the k th variable in the t th generation.

D. The impact of collecting behaviour on fleet navigation

$$c_k^t=\text{Collection}_j^t+c^t \tag{7}$$

$$d_k^t=\text{Collection}_j^t+d^t \tag{8}$$

Where c^t represents the minimum value of all variables in the t th generation; d^t represents the maximum value of all variables in the t th generation; c_k^t is the minimum value of fleet k in the t th generation; d_k^t represents the maximum value of fleet k in the t th generation; Collection_j^t represents the position of the j th collection point selected in the t th generation.

E. Adaptive dynamic adjustment of collection point influenceE.

$$c^t=\frac{c^t}{I} \tag{9}$$

$$d^t=\frac{d^t}{I} \tag{10}$$

where I is the scale factor. In the actual exploration process, the collection point size does not become steadily larger with increasing iterations, and under the influence of the risk of human destruction and natural disasters, there is a possibility of solidification, shrinking, or even phase disappearance and complete destruction after the focus of the exploration field changes, so it needs to respond to the collection point capacity dynamically. Wu Weimin et al. propose a strategy regarding the adjustment of the I parameter in the Antlion algorithm, based on the collection point capability ($p=\frac{N_{\text{col}}}{N}$, $N_{\text{col}}$the number of fleets collected by the collection point in the last iteration) compared to a reference quantity 1/5. When the capability is greater than the reference amount, it proves that the influence of the collection point exceeds the expectation and the global influence should be expanded; when the capability is equal to the reference amount, it means that the global influence and local influence reach the balance; when the capability is less than the reference amount, it means that the influence of the collection point fails to reach the expectation and the local influence should be improved. The I factor is adjusted as follows.

$$I(t)=M(t)\cdot\frac{10^3 t}{t_{\max}} \tag{11}$$

$$M(t)=\begin{cases}M(t-1)\cdot M_a,\ p>0.3\\ M(t-1),\ 0.2\leq p\leq 0.3\\ M(t-1)/M_a,\ p<0.2\end{cases} \tag{12}$$

where$M(1)=1$; $M(t)$ is the modulation factor for the size of the influence; M_a is a constant value greater than 1, called the learning factor of $M(t)$, which controls how proactive the algorithm is in adapting to the environment.

F. Fleet mooring and collection point construction

When a convoy is moored to a collection point, if the fitness of a convoy becomes higher than the fitness of the ant lion, the convoy is considered to be moored to the collection point and data migration behaviour occurs. In order to increase the number of new attractive moorings and opportunities for data collection, new collection points are gradually created along the route of the fleet, which is also known as the antlion trap location update behaviour in the antlion algorithm.

$$\text{Collection}_j^t=\text{Fleet}_k^t\quad f\left(\text{Fleet}_k^t\right)>f\left(\text{Collection}_j^t\right) \tag{13}$$

where t is the current number of iterations; Fleet_i^t is the position of fleet i in the t th generation; Collection_j^t is the position of collection point j in the t th generation; and f is the fitness function.

G. Elite collection point updates

The best adapted collection point is used as the elite collection point, which will influence the sailing behaviour of all fleets. Assuming that the navigation of each fleet is influenced by both the collection point chosen by the roulette strategy and the elite collection point, the position of fleet i in generation $t+1$ is

$$\text{Fleet}_i^{t+1}=\frac{R_A^t(l)+R_E^t(l)}{2} \tag{14}$$

where $R_A^t(l)$ is the value generated by l th step of navigation around the collection point selected by the t th generation roulette strategy; R_E^t is the value generated by the l th step of navigation around the elite collection point in the t th generation; and l is the number of navigation steps.

The algorithm is based on Wu et al.'s proposal to introduce a population improvement rate feedback feature Δ and an elite Gaussian variation strategy to address the shortcomings of the basic Ant-Lion algorithm in terms of missing partial optimal solutions and local optimal solutions due to premature maturation of the algorithm. The calculation principle is: the ratio between the absolute value of the best collection point fitness value obtained in this iteration and the best collection point fitness value in the n th previous iteration, and the ratio of the best collection point fitness in this iteration, is within the range Δ, then the population improvement does not reach the expected value, then Gaussian variation is performed.

$$\frac{\left|fit\left[X_{\text{best}}(t)\right]-fit\left[X_{\text{best}}(t-n)\right]\right|}{fit\left[X_{\text{best}}(t)\right]}\leq\Delta,\ t\geq 10 \tag{15}$$

$$X_{\text{best}}(t)=X_{\text{best}}(t)+\beta N(0,1) \tag{16}$$

where β is the coefficient and $N(0,1)$ is the standard Gaussian variance random number.

H. Fleet mooring and collection point construction

The case study selected 216 image resources in professional map (navigation) resources from the 14th-16th centuries, and manually read 37 points among them that could be discerned to confirm port points. Based on the map release chronology, we compiled management rules based on origin, landing discovery, port construction, agency management, and data sub-center tags. Combined with data such as fleet exploration routes, colonization point construction information, and trade transaction records, effective organization of data is realized, and algorithmic intervention is implemented.

As the research landing point of this paper is the recognition of iterative approach in the face of knowledge data production and the role of iterative thinking positioned through algorithmic empowerment, the main features can be summarized to include at least the following aspects:

1) *Uncertainty of goals:* Environmental orientation becomes an important exogenous factor influencing the accumulation process of geo-knowledge data. Geo-data itself has a strong external interaction, and the process of clarifying the goal is usually a process of continuous interaction with the environment. Demand and information as input and output variables are relatively uncertain in themselves, and need to be identified, judged, converged, and made explicit. Inputs and outputs from the environment need to be continuously introduced and modified around the goal. At the same time, the results are counteracted to the goal to further clarify it.

2) *Tentativeness of behavior:* The constant approach to the goal requires constant experimentation, selection, critique, and elimination. Especially for the old and innovative parts, it needs to be constantly debugged and tested and measured. Therefore, the whole process of problem solving is also a process of data optimization and convergence of exploration paths.

3) *Periodicity of the process:* The iterative process of geo-knowledge is a kind of innovation process, full of quantitative to qualitative leaps. Corresponding to each large and small qualitative change, the iterative process of knowledge also generates large and small cycles. Each cycle can constitute a loop, and the nodes during the cycle are measurable test and control points.

4) *Process nature of production:* Knowledge product development activities are more process-oriented and increasingly diversified and have become a complex system engineering under the backdrop of demand. The production and release of nautical charts focus on process reengineering and process control, effectively solving the process, carrying out internal service technology innovation and implementing the whole management of the problem directly enlightened the timing technology and cartography. The introduction of the "process" concept into the knowledge product development work can be seen as a data hub with distributed data acquisition constantly causing the global optimum of data, triggering iterative thinking on knowledge product engineering development activities.

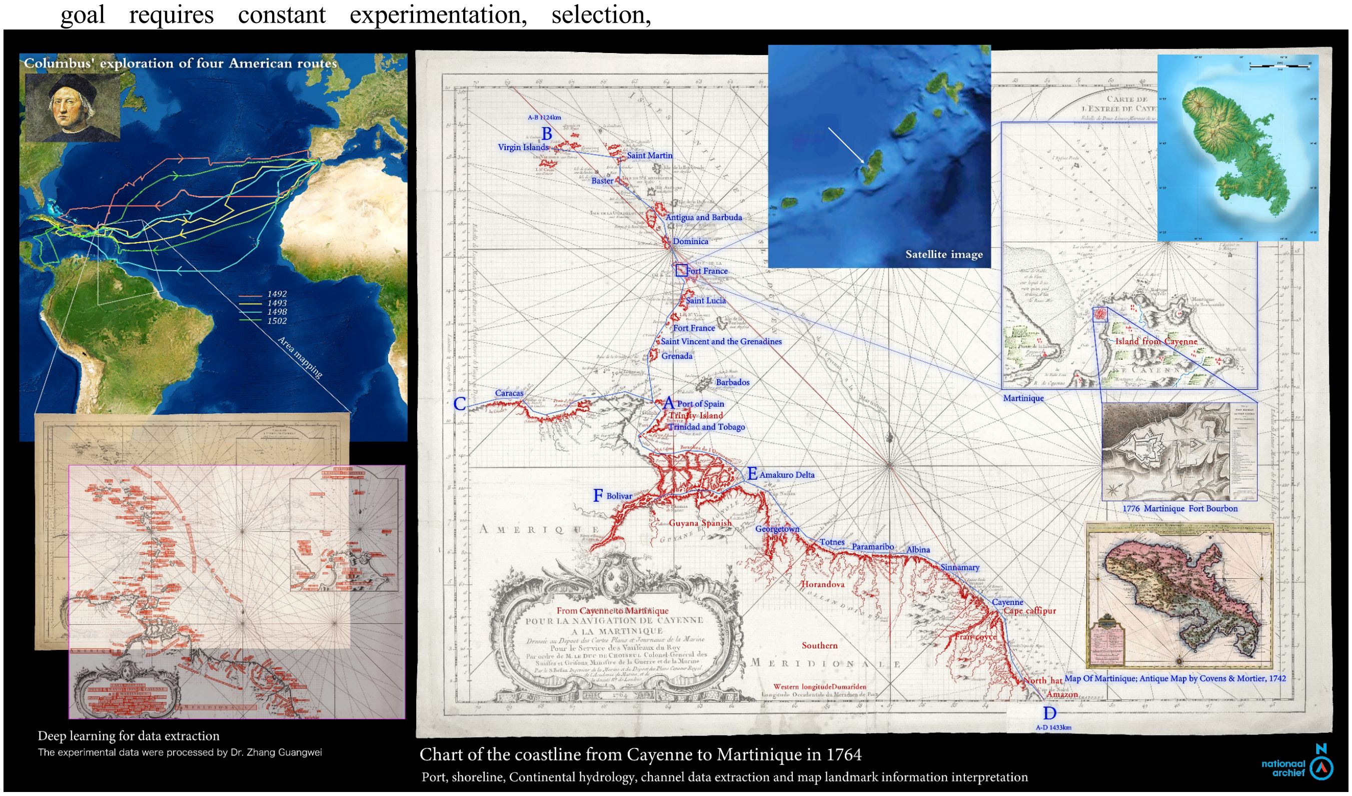

Fig. 1. Deep learning for data extraction

V. CONCLUSIONS AND FUTURE WORK

The nautical chart algorithm referred to in this paper encompasses the entire process of prior analysis, design, construction, implementation, and delivery of knowledge data production. The characteristics of recent knowledge production and iterative thinking distilled through the study provide us with an applicable methodology to guide the productization work. The knowledge data production in the era of geographic discovery empowered by nautical chart algorithms has the following characteristics.

Uncertainty in the demand for knowledge production. There are immediate, medium-term, and long-term needs, as well as explicit, implicit, and potential needs. Medium- and long-term needs and implicit and potential needs are often insufficiently determined. User satisfaction, as a measure of demand satisfaction or service effectiveness, also has considerable uncertainty, including the conditionality of demand environment, time and space conditions, usage, etc., the subjectivity of user knowledge background, user willingness, user experience, etc., and the evolution of various changes that may occur with the development of events.

Knowledge production and expression is data-bearing. Knowledge in solidified form needs data-carrying expression. No matter the expression of explicit knowledge or tacit knowledge, it cannot reach the efficacy of data existence, and the process of continuous revision of knowledge data is highly agile.

Knowledge production is intellectually creative. Knowledge data production is not only the process of data intelligence acquisition, but also induction, summarization, and reasoning, and moreover, experiments, explorations, and attempts to continuously promote method innovation, model innovation, and knowledge innovation.

Knowledge production has a life cycle. The production of knowledge data has distinctive characteristics of the times, and only by starting from the market demand and its trend changes, keeping abreast of the times according to the development law of the industry field, and constantly improving the production process, can we ensure the advanced and practicality of the products.

The nautical chart algorithm focuses on the research of the feedback strategy with the knowledge production behavior, and there is a need to continue the evolution in the fine-grained and reusability of the research, such as the feedback algorithm in the four-stage traffic prediction model, which can iterate through the cycle until convergence or reach the maximum set number of cycles of the model, and the iterative calculation of travel cost is introduced in the cycle calculation process, etc. It should be considered in the next stage of improvement. At this stage, although the present algorithm is effective in the organization of data samples and the extrapolation of phenomena in the face of long-time, multi-objective dynamic path planning, it will be difficult to accept the running time when directly applied to the analysis of global integrated traffic models under the challenges of increasingly complex data classes, urgent surge in data volume, and more refined target partitioning, and the problems in rapid response are particularly For this reason, it is necessary to further optimize the algorithm model structure to seek higher model efficiency.

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