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A Multi-Objective Dynamically Optimized Fleet Algorithm for Misty Fields Exploration

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***Abstract*—The Fleet algorithm is a new meta-heuristic swarm intelligence algorithm inspired by the behavior of fleet exploring unknown regions, collecting and distributing geo-data and deciding on global voyage data acquisition in the Age of Discovery. To address the problem of solving the optimal path for multi-objective path planning in the exploration of the misty aread, this paper proposes and constructs a dynamic path planning model for a fleet of ships exploring global route geo-data. The global optimal path can be effectively planned by fitting the algorithm model description with the historical archival data for deduction.**

Keywords-fleet algorithm; intelligent evolution; social computing; group intelligence

I. Introduction

Currently, social computing research focuses on social modelling of individuals and groups, socio-cultural modelling and analysis, analysis of social interactions and their laws, social data perception and knowledge discovery and decision support and applications. In the practice of intelligent evolutionary computing with the goal of understanding the pattern of social evolution, the vast majority of research relies on the analysis of textual data, and less often applies to social modelling computational methods, with the problem of difficult experimental analysis and evaluation [1]. To address the dilemma of experimental analysis of complex social systems, Chinese scholars propose the ACP method of "artificial society + computational experiment + parallel execution" based on the basic model of sociology, which adopts a top-down modeling method of intelligences for portraying emergent behaviors in social events [2]. The ACP approach uses a top-down intelligence modelling approach to portray emergent behavior in social events; it exploits the designability and repeatability of artificial social computational experiments to quantify the evolutionary patterns responsible for social events through artificial systems involving different experimental scenarios. In the practice of intelligent evolutionary computing, which aims to understand the laws of social evolution, the complexity of human social behavior and its data and the chaotic nature of dynamic rules lead to a deep fog in which the vast majority of behavior is not visible and obvious.

It is foreseeable that computational experiments on artificial societies will be widely used in various studies on social computing in the near future, simulating social evolution through computational experiments and providing a reference basis for discovering the patterns of social evolution and cultural evolutionary characteristics. However, due to the complexity of real human social behavior and its data, and the chaotic nature of the dynamic rules, social computing research is still facing major difficulties: for example, the goal of constructing artificial social models is far from the complex reality; a large amount of data is hidden in the vast amount of canonical texts, which cannot be involved in social modelling calculations, etc.

In response to the above problems, this paper proposes an evolutionary model of social knowledge evolution based on the ant colony optimization algorithm, taking the example of the fleet exploration in the geographic discovery of the age of navigation, which provides a coupling idea for the participation of textual historical materials in complex social computation. The paper firstly compares and introduces the characteristics of the geographic discovery in the Age of Sail; secondly introduces the improvement objectives and principles of the fleet algorithm; then proposes a fleet exploration model based on the ant colony algorithm; then introduces the application of the fleet exploration model with specific cases; and finally summarizes the shortcomings of the current research and the expectations for future algorithm improvement.

II. MOTIVATION

This section provides an introduction to the geographical knowledge evolution process of geographical discovery in the Age of Discovery, analyses the rationale for the application of intelligent computing to the analysis of fleet behavior, and presents the application of evolutionary algorithms to this problem in the context of the realities of the problem.

A. The realization of geo-exploratory behaviour in the problem of knowledge evolution

Geopolitical knowledge exploded during the Age of Discovery and geographic discoveries. The research addresses this phenomenon by developing an evidence-based interpretation of behavior. It can be found that the geo-knowledge generated in early land exploration relied on the shifting of road networks, the migration of communities, commercial trade and conflict for thousands of years. However, that phase has been frozen for a long time under the pressure of regional geopolitics. Along with political-military behavior, there is even a negative trend in the evolution of geo-cognition, data accuracy and total knowledge.

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Geopolitics has placed constraints on the evolution of common global knowledge.

The urgent need to open up ocean routes and explore new continents thus became a consensus among Western nations, and at the same time the strongest driving force in the evolution of geo-knowledge. In the early days of maritime exploration, the tools of navigation were relatively rudimentary and the exploratory behavior of fleets was in a state of blindness, but the total amount of knowledge grew and the precision of the data intensified. Ocean exploration was deeply coupled with land reclamation, port construction, trade exchanges and military behavior, and with a series of acts such as route solidification, data structure solidification and geo-knowledge exchange, mankind finally completed the basic knowledge of global geo-territory.

The above process depicts the motivation, production, sharing, application and evolution of the geo-information of the Great Geographic Discovery. By exploring the evolution of knowledge in the geographic discoveries, the implied development of civilization and the code of human evolution can be discovered, which is of great significance for exploring the nature of human social evolution.

B. Exploring the Misty Fields

In the 1990s, M. Dorigo proposed a completely new ant colony optimization (ACO) algorithm that simulates the behavioral science of nature, with parallel computing and robustness. "Any problem in computer science can be solved by another layer of indirection", and stochastic ranking methods based on the treatment of constraints have been proposed, which can reduce the traditional, composite penalty function with Lagrange's equation into a simple ordering, which has been empirically proven to achieve good practical application at the expense of partial mathematical convergence.

After an in-depth investigation of global geo-exploration events in the Age of Discovery, this paper chooses to use fleet behavior as the basis of the algorithm to develop the following analysis: First, in early exploration, fleets lacked the support of detailed nautical data and had vague voyage goals. However, based on large-scale exploration behavior, the frequency of voyages, the total number of ships and the direction of exploration are continuously optimized, where the optimal fleet can basically achieve the revenue goal (whether it is geographical discovery or logbook or economic revenue). Secondly, each time the optimal fleet explores a path, it is a feasible path from the port to the target. Once the target is discovered and marked by the optimal fleet, the other fleets quickly follow the same route in groups to reach the destination. In this case, the other fleets do not choose the feasible paths unconsciously, but there is information transfer between the fleets - position data and route data. Thirdly, during the voyage the fleet would scientifically record 'geo-information' to mark its path. In the process of exploring the New World, the fleet will generally choose the direction of exploration based on the validity and density of this kind of geo-information. It is this special way of transmitting information that allows the fleet to reduce disorientation and ultimately achieve the best possible results in terms of getting to where they are.

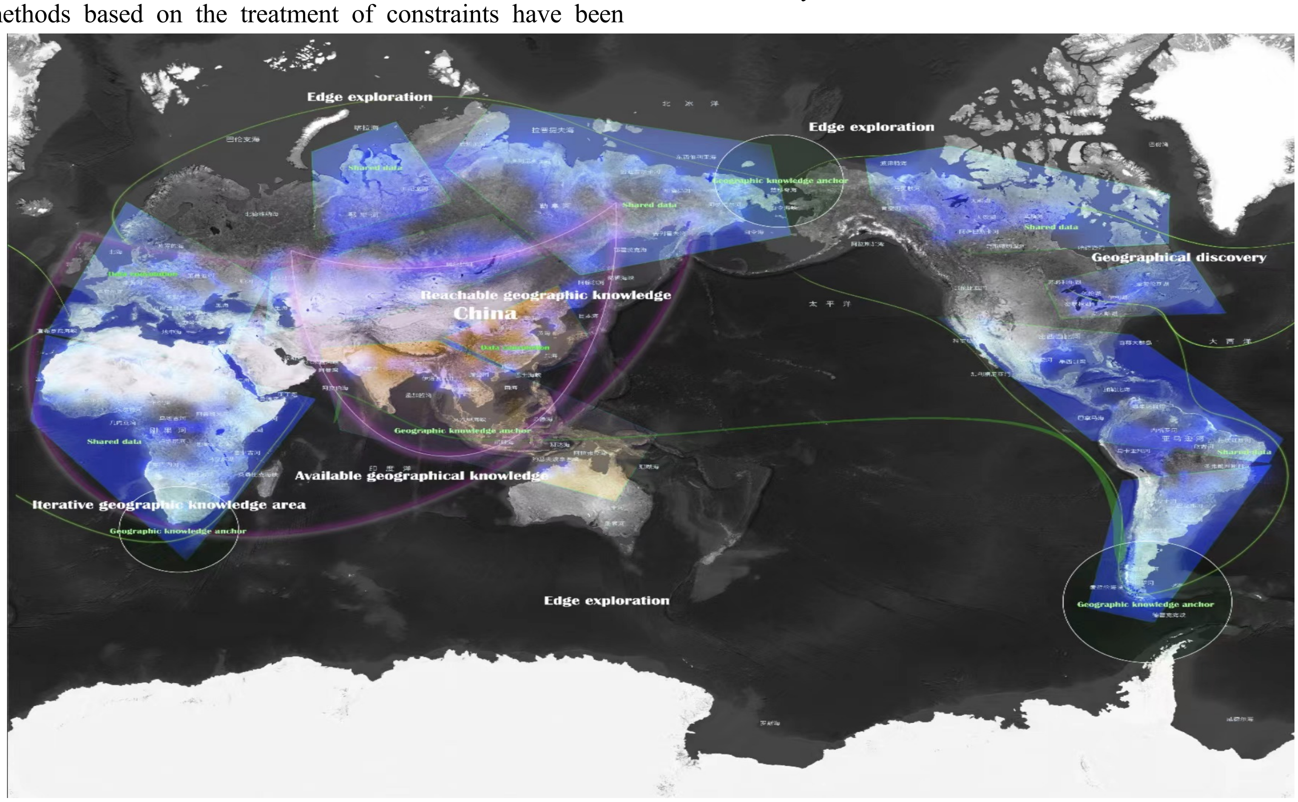

Fig. 1. Fleet exploration and convergence of route data

C. Evolutionary Computation and Genetic Algorithms

Evolutionary computation implements global probabilistic search based on biological evolutionary mechanisms such as natural selection and genetic variation to find an approximate global optimal solution to a problem without requiring the function to be continuous, differentiable and single-peaked. This feature guarantees the solvability of evolutionary computation and neural network research in solving multimodal optimization problems. Today, evolutionary computation has emerged as a branch of research in genetic algorithms, evolutionary programming, evolutionary strategies and genetic programming, and is widely used in NP and NPC problem solving, neural network optimization, multi-objective optimization problem solving and many other fields, and has been deeply involved in the frontiers of computer science and artificial intelligence research.

In 1975, John Henry Holland of the University of Michigan proposed "genetic algorithms", drawing on the ideas of Darwinian biological evolution and Mendel's laws of heredity. It starts with a certain number of initial points, each with randomly generated characteristics, and the successfully generated nodes are merged into a new 'intelligence'. This intelligence has biparental characteristics and meets the premise of "adaption", which supports adaptive search of computational programs [3]. The use of evolutionary ideas in the optimization of computer functions provides a mechanism for computers to adapt and learn through "reproduction", providing a new pathway for studying the space of evolution and natural phenomena.

In this study, in order to build the basis for a social evolution algorithm, a refinement of the Ant cycle concept with the possibility of adaptive ACOs was chosen for the study.

In the 1990s, M. Dorigo proposed a new Ant colony optimization (ACO) algorithm that simulates the behavioral science of nature, with parallel computing and robustness. In this study, in order to build the basis for a social evolutionary algorithm and to analyze how human thinking and behavior form the driving force for exploring the unknown, a modified Ant colony algorithm with the concept of Ant cycle and the adaptive possibilities of ACO are chosen for the study [4].

III. Algorithm Building Principles and Improvement Goals

A. Improvement objectives for the ACO base algorithm

In all social evolutions, intelligences learn based on structure when acquiring knowledge. Most deep learning models are also first designed with structure and then trained with weights. In the process of intelligent learning, however, no social behavior or brain-like thinking can be optimally solved by relying on one fixed structural model and considering only variation in weights. The inherent complexity, multi-objective characteristics and variability of social behavior all contribute to the practical difficulties of placing too much emphasis on algorithmic adaptation.

Intelligent algorithms can greatly accelerate the avoidance accuracy of path exploration and planning in experimental data [5], but at the same time the combination of the information positive feedback principle and heuristic algorithms, which utilize random selection strategies in the process of constructing solutions, affects the speed of evolution, and the positive feedback principle, which aims to reinforce locally optimal solutions, is highly susceptible to stagnation [6][7]. An improved model of the ACO algorithm is constructed using the behavior of a fleet of ships exploring global location targets as inspiration, firstly to analyze the limitations of the underlying ACO algorithm and to improve it by:

1) *Slow convergence of the algorithm initially:* The initial values of the geo-edge data in the fleet algorithm are the same, and the selection of the next node tends to be random. Although random selection explores a larger task space and helps to find potentially globally optimal solutions, it takes a longer time for the positive feedback to take effect, resulting in a slower convergence rate of the algorithm initially [8].
2) *Local optimality:* Even with the positive feedback feature, since the geoid information is identical in the initial space-time and the fleet completes the construction of solutions in an almost random manner, these solutions are bound to be superior or inferior. As the geo-data is continuously updated, the fleet algorithm leaves more geo-data on the paths through which the better solution passes, and more geo-data in turn attracts more fleets to join the exploration, a positive feedback process that rapidly widens the initial differences and guides the whole system to evolve towards the optimal solution [9][10]. Although positive feedback gives the algorithm a good convergence rate, if the algorithm starts with a suboptimal solution, then positive feedback can cause the suboptimal solution to dominate quickly, causing the algorithm to fall into a local optimum and make it difficult to jump out of the local optimum.
3) *Improving optimization capabilities*: The ACO base algorithm describes the correlation of parameters and logical genes, but parameter selection relies more on experience and trial and error, and inappropriate initial parameters can weaken the algorithm's optimization capability. This is why in fleet exploration for path planning, taboo tables are set in the algorithm to avoid forming circular paths or repeated visits to certain nodes. Taboo tables can easily cause "deadlocks", which can affect the optimization efficiency of the algorithm.
4) *Resolving the conflict between fleet diversity and speed of convergence*: The diversity of the fleet corresponds to the distribution of candidate solutions in the problem space. The more uniform the distribution of individuals, the better the diversity of the population and the higher the probability of obtaining the global optimal solution, but the longer the search time; the more concentrated the distribution of individuals, the poorer the diversity of the

population, which is not conducive to the exploration ability of the algorithm [11]. Positive feedback can speed up the convergence of the algorithm, but makes the algorithm focus on some of the candidate solutions earlier, so positive feedback reduces the diversity of the population, and is not conducive to improving the algorithm's global search ability.

B. The construction of taboo algorithms in feasible solutions

The fleet algorithm involves the act of fleet exploration in geo-knowledge, not as an isolated, context-free action, but as a complex act where there is a specific search direction objective, a group cognitive exploration purpose, and a need to take into account multi-objective dynamic optimization results in a "fog" [12]. 1986, the taboo search algorithm TS (Tabu Search) was proposed by Professor Fred Glover of Colorado State University, USA, as a search method to jump out of the local optimum.

Taboo search, a sub heuristic stochastic search algorithm, can start from an initial feasible solution and select a series of specific search directions (moves) as a trial, choosing the move that achieves the most change in the value of a particular objective function. In order to avoid getting trapped in a local optimum, a flexible 'memory' technique is used in TS search to record and select the optimization process that has been carried out and to guide the next step in the search process [13]. Forbidden search is based on domain search by setting up a forbidden table to forbid some operations that have already been performed, and using a contempt criterion to reward some good states, which involves key factors affecting the performance of the forbidden search algorithm such as neighborhood, forbidden table, forbidden length, candidate solutions and contempt criterion.

In implementing the fleet algorithm to solve for the optimal path to explore the misty area, each fleet roams with a certain probability. The reason for the roulette algorithm and the cumulative probability of the fleet choosing the next port is to increase the chances of expanding other routes. In the early days of exploration, geo-data was not sufficiently accumulated and fleets chose their sailing routes randomly. Initially, each sailing route has the same level of geophysical knowledge, so the probability of choosing which route to take is the same. After a certain amount of geo-data has been accumulated, the probability of the next exploration target chosen by the fleet is determined by a combination of factors such as distance, amount of geo-data and exploration value.

To minimize the generation of invalid data, fleets are assigned a taboo table, which records the current set of points travelled by the fleet to avoid repeated exploration of an area. For any fleet, the exploration process is bounded by a life cycle in which 1) the fleet successfully reaches the departure point of another group of fleets, at which point the fleet explores a navigable path; 2) the fleet meets another fleet during its exploration, and if the locations explored by any two fleets do not overlap (except for the meeting point), the paths travelled by the two fleets are connected and can constitute the exploration of a navigable path; 3) the fleet is unable to find a landing area unless it returns along the original route.) the fleet is unable to find a landing area, unless it returns one or more journeys along the original route and cannot continue exploring, the fleet's act of exploration ends.

C. Geophysical information and supplementary variables

The geo-geographical knowledge produced during the fleet exploration process, especially the location information, i.e. the "fog", is deciphered by the exploration behavior and is considered as the "visible" area. Therefore, as time accumulates and the number of participating fleets increases, the "fog" area is compressed by the fleet exploration. As time accumulates and the number of participating fleets increases, the "foggy" area is continuously compressed by fleet exploration, and the act appears in the form of geo-geographic data production, the information data should also exist to accelerate the feedback and increase the efficiency of dissemination, thus inducing the upgrade of data processing arithmetic and knowledge services, which will be fed back to the sailing act again [14][15].

The goal is to clear the 'fog' of global geo-geography, i.e. to build a knowledge evolution of the basics of global geographic discovery, such as continental coastlines described by global latitude and longitude networks, global shipping routes, maritime meteorology, estuarine waterways, distance data, etc. Behavioral supplementary rules were constructed in the study to add three variables to the fleet model study, the global voyage objective, the consolidation objective and the risk objective. The differences are as follows:

- The global route target model requires an updated evaluation of the validity of position information on all paths after implementing a circular structure of position data with global data.
- Consolidation and risk objectives require local information, i.e. the position data on the path needs to be updated with the global evolutionary data after a vessel has completed a step. The updated position data information will only be available when all vessels have completed a path cycle of exploration. Therefore the position data information on the path should be divided into two parts: the position information of this exploration that has occurred without integration and the position information left by all vessels that have passed through the path after the current cycle.

IV. Fleet Algorithm

This section introduces the calculation method of the fleet exploration model based on the above algorithm improvement objectives and principles. The specific parameters are adjusted and explained for the specific characteristics of the fleet exploration problem, and the application effect of the algorithm is introduced with specific cases.

A. Fleet system description

The fleet explores the optimal global route in the raster map. The optimal global route is the route that visits all ports and has the shortest sailing distance. The raster map is divided into land area and navigation area. The land area includes land interior points and land edge points. The land interior points are not accessible, and the land edge points can be docking points for the fleet. Navigational domain is the area where the fleet explores and navigates.

Fleet behavior is divided into navigation behavior and docking behavior. The fleet selects target locations according to certain strategies (amount of geo-data, visibility and exploration value) and completes visits to all target locations in the order of strategies. During the voyage, additional geo-data volume is generated according to the unit length. A strategy to control the distance from land edge points should exist during the course of the fleet voyage to ensure that it is not too far offshore (to facilitate resupply and improve accuracy of geo-data recording) and not too close offshore (to ensure navigation efficiency). When the flotilla sails to a certain number of times it needs to stop to land for resupply. When the number of moves reaches the threshold, the fleet will choose the nearest land point to stop for resupply, update the number of moves and continue to the target location. If the fleet cannot dock to a land edge point even when the maximum number of moves is reached, the fleet is destroyed and the amount of geo-edge data generated and the amount of new docking points are not recorded. The docked land edge points are added to the destination surface and added as new destinations in the next iteration. Each time the fleet stops at a land point or visits a port, the amount of path geopathic data is updated. When the entire fleet has finished a voyage, the geo-edge data values of each path are updated and new destination locations are added for the next iteration.

Table 1. Fleet System Symbol Description

Symbols	***Meaning***
$f(w)$	Objective function
w	A solution to problem
P_{ij}	The probability of the fleet travelling from port i to port j
τ_{ij}	Geopathic data intensity of path (i,j)
η_{ij}	Visibility factors in calculating the port visit sequence
γ_{ij}	Port attractiveness factors of port visit sequence
ψ_{ih}	Visibility factors of move between adjacent grids
d_{ih}	Distance between grid i and grid h
$movenum$	Number of fleet movements
$berthnum$	Number of movements during the fleet's finding supplies
threshold	Threshold for fleet conversion from exploration to docking
visual	Fleet visual range
n	Number of ships visiting a port in this iteration

B. Objective function and optimal solution

The objective function is the sum of the total lengths of all paths $f(w)$, $w = (i_1, i_2, \cdots, i_n)$ for an arrangement of ports 1,2,⋯n, $i_{n+1} = i_1$.

$$f(w) = \sum_{l=1}^{n} d_{i_{l-1} i_l} \tag{1}$$

Let the optimal solution w^* correspond to the time variable t^*, and a solution *w* corresponds to the time variable *t*. When a solution *w* is obtained, the optimal solution t^* corresponds to the time variable t^* and the objective function value $f(w^*)$ is updated as follows.

$$w^* = \begin{cases} w, & f(w) < f(w^*) \\ w^*, & f(w) \geq f(w^*) \end{cases} \tag{2}$$

$$t^* = \begin{cases} t, & f(w) < f(w^*) \\ t^*, & f(w) \geq f(w^*) \end{cases} \tag{3}$$

$$f(w^*) = \begin{cases} f(w), & f(w) < f(w^*) \\ f(w^*), & f(w) \geq f(w^*) \end{cases} \tag{4}$$

C. Rasterized Navigation Map

Assume that the fleet is moving within a two-dimensional rasterized world map with a finite number of land obstacles of different sizes distributed in the region. A right-angle coordinate system is established in the region. The fleet moves with a certain step length *L*. The grid units of the *x* and *y* axes are *L*. The fleet moves one grid at a time. The number of grids per row is $N_x = x_{\max}/L$, and the number of grids per column is $N_y = y_{\max}/L$. If the land shape is irregular, the land raster is added at the boundary, and one or more rasters are used to represent the land, and less than one raster is counted as one raster. The inner land grid is set as inaccessible forbidden grid, and the land edge grid (at least 2 of the neighboring grids are feasible) is accessible and can be used for ship docking.

The relationship between the corresponding coordinates (x_1, y_1) of each grid and the sequence number i is expressed as

$$\begin{cases} x_i = [(i-1) mod N_x] + 1 \\ y_i = \mathrm{int}[(i-1) mod / N_x] + 1 \end{cases} \tag{5}$$

Assume that the fleet can only move between adjacent grids each time, and any grid has 8 adjacent grids, i.e., top, bottom, left, right, top left, top right, bottom left and bottom right. The fleet can move to the center of the grid each time it moves. The fleet reaches a target port after several moves and visits all the ports to be visited in the path vector one by one, finally ending a voyage.

To solve the path deadlock problem, when grid i's only neighbor grid j is reachable, grid i is path deadlocked and it is classified as a forbidden grid and considered as an obstacle. When raster i is the only reachable neighbor raster of forbidden raster j, then raster i is classified as an emergency raster and considered as an obstacle. Meanwhile, in order to keep the search process away from the space that is least likely to produce a better solution and reduce the generation of inferior solutions, when raster i has only two reachable neighbors j and s, if the angle between the path (i, j) and (i, s) is equal to 45°, raster i is classified as a forbidden raster and considered as an obstacle.

D. Determining the order of port visits

$$P_{ij}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)\gamma_{ij}^{\theta}(t)}{\sum_{s\epsilon\text{allowed}_k}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)\gamma_{ij}^{\theta}(t)}, & s\epsilon\text{allowed}_k\\ 0, & else\end{cases} \tag{6}$$

Where $P_{ij}(t)$ is the probability that the fleet travels from port i to port j. $\tau_{ij}^{\alpha}(t)$ denotes the strength of the geo-data volume between *i* and *j*. α reflects the relative importance of the geo-data volume accumulated by the fleet during the voyage; $\eta_{ij}^{\beta}(t)$ denotes the path visibility (the reciprocal of the distance d_{ij} between *i* and *j*, β reflects the relative importance of port distance in path selection; $\gamma_{ij}^{\theta}(t)$ indicates the attractiveness of the port (the ratio of the number *n* of fleets visiting the port in the previous generation to the total number *N* of fleets in the last iteration), i.e., the fleet's evaluation of the exploration value of going to the port, θ reflects the exploration value of the sailing destination relative importance in path selection. A taboo table is set for fleet voyages, which does not allow the fleet to consider ports that have already been visited. Construct the path memory vector of the route for each fleet.

$$\eta_{ij}^{\beta}(t)=\frac{1}{d_{ij}} \tag{7}$$

$$d_{ij}=\sqrt{\left(x_i-x_j\right)^2+\left(y_i-y_j\right)^2} \tag{8}$$

$$\gamma_{ij}^{\theta}(t)=\frac{n}{N} \tag{9}$$

E. Fleet navigation control

Each fleet movement can only be made between adjacent grids, and any grid has 8 adjacent grids, i.e. top, bottom, left, right, top left, top right, bottom left and bottom right. The fleet can move to the center of the grid each time it moves. After several moves, the fleet reaches a current target port and visits all the ports to be visited in the path vector one by one, finally ending a voyage. If there is an intermediate stop for resupply, it departs from the stopping point to the current target port after resupply.

5) The distance between any grid i and the adjacent grid h is d_{ih}, where x and y are the grid coordinate information. Since the fleet can only move one frame at a time, the value of d_{ih} is 1 or $\sqrt{2}$.

$$d_{ih}=\sqrt{(x_i-x_h)^2+(y_i-y_h)^2} \tag{10}$$

6) The distance between any raster *i* and the current target port *j* is d_{ij}, where x and y are the raster coordinate information.

$$d_{ij}=\sqrt{\left(x_i-x_j\right)^2+\left(y_i-y_j\right)^2} \tag{11}$$

7) The distance between the grid i in which the fleet is located and all land points in the visual range centered on the fleet itself is d_{iB},where *x* and *y* are the grid coordinate information.

$$d_{iB}=\sqrt{(x_i-x_B)^2+(y_i-y_B)^2} \tag{12}$$

8) The visibility for moving paths between adjacent grids (i,h) is expressed as $\psi_{ih}(t)$, where k_1, k_2 and k_3 denote the weights of the three distances. Where d_{ij} is added to avoid moving away from the target direction and to speed up the convergence of the algorithm; d_{iB} is added to control the offshore distance of the vessel navigation.

$$\psi_{ih}(t)=\left(\frac{1}{d_{ih}}\right)^{k_1}\cdot\left(\frac{1}{d_{ij}}\right)^{k_2}\cdot\left[\frac{1}{1+(d_{iB}-\text{visual})^2}\right]^{k_3} \tag{13}$$

9) The fleet is selected to travel to a grid h among adjacent optional grids with probability P_{ih}. where $\tau_{ij}(t)$ is the geo-data volume intensity, α reflects the relative importance of the geo-data volume accumulated by the fleet during the voyage; $\psi_{ih}(t)$ is the visibility of the moving path, φ reflects the relative importance of visibility.

$$P_{ih}(t)=\begin{cases}\dfrac{\tau_{ih}^{\alpha}(t)\psi_{ih}^{\varphi}(t)}{\sum_{s\epsilon\text{allowed}_k}\tau_{is}^{\alpha}(t)\psi_{is}^{\varphi}(t)}, & s\epsilon\text{allowed}_k\\ 0, & else\end{cases} \tag{14}$$

F. Geo-data update

Geopolitical data updates occur when a fleet of ships calls or visits a port after a number of movements. When a fleet visits a port, it exchanges with the port some or all of the amount of geo-data generated during the previous leg of the journey, and this geo-data has an impact on the actions of subsequent visiting vessels.

The amount of geo-data on the path (i,j) route raster after a fleet *k* has docked or visited port *j* from *i* is adjusted as:

$$\tau_{ij}'=\rho\cdot\tau_{ij}+\Delta\tau_{ij}' \tag{15}$$

$$\Delta\tau_{ij}'=\sum_{k=1}^{m}\Delta\tau_{ij}^{k}{}' \tag{16}$$

$$\Delta\tau_{ij}^{k\prime} = \begin{cases} \frac{Q}{L_k} & \text{Fleet } k \text{ passed through the path } (i,j) \text{ in one voyage of } n \text{ steps} \\ 0 & else \end{cases} \quad (17)$$

where τ_{ij}' is the amount of geo-data left on the path after the convoy k path (i,j); $\Delta\tau_{ij}'$ is the total amount of geo-data increase on the path (i,j) in this iteration; ρ is the damage factor of geo-data ($\rho = \text{rand}[0,1]$). Q is the amount of geo-data generated by the fleet after a number of moves through the path (i,j) length L_k.

G. Fleet docking

When the number of movement $movenum$ reaches threshold, the fleet will choose a straight line to the nearest land point within the *visual* range of the fleet itself. If the land point is not reached after *berthnum* moves, the fleet will be considered damaged and will not move forward.

$$erthnum = \mu\text{threshold} \quad (18)$$

$$\mu = \text{rand}(0,0.5) \quad (19)$$

After the fleet arrives at a land point, if the land point is already in the port list, $n = n + 1$ and the port attraction is enhanced; if the land point is not in the port list, the land point is added to the port list and the land point is noted as the port point in the next iteration with $n = n + 1$. The fleet updates $movenum = 0$ and $berthnum = 0$, updates the geo-data intensity according to 4.6, and then departs again for the current target location.

H. Steps of fleet algorithm implementation

According to the above definition and rules, the steps for solving the global route path planning problem with the fleet algorithm are described as follows.

1) Initialize the raster navigation map, improve the map environment according to rule *E*, and add the forbidden raster.
2) Initialize each path geo-information intensity C_0 according to the greedy algorithm, and $f(w) = f(w^*) = f(0)$.
3) Initialize the number of iterations $t = 0$.
4) Initialize m fleets in p ports, generate random thresholds for each fleet at random, initialize each fleet with $movenum = 0$ and $berthnum = 0$.
5) Add the initial cities of all fleets to the taboo table $tabu_k$.
6) Determine the target port order for the fleet sailing according to *D*.
7) Move the fleet to the next grid according to *E*.
8) If the fleet has completed this voyage, let $t = t + 1$, update the geo-data strength according to *F* and execute step 9. Otherwise, if the number of fleet movements reaches threshold, make a stop for resupply according to *G*. Otherwise, return to execute step 7.
9) Update w^*,$t^*$and $f(w^*)$according to *B*.
10) If t is less than the specified number of iterations, return to step 4; otherwise, output w^* and end.

I. Case

Since the 15th century, geographic discoveries have led to the emergence of new information on the records of global positions acquired in Europe, and people finally broke free from the repression of the old frames and sought new answers. The great geographic discoveries proved that the earth is round and also confirmed the existence of vast oceans on the earth, and clarified the basic outline of sea and land, clarified the shape, size and form of movement of the earth, collected and accumulated a large amount of marine, biological and geological information, which caused new thinking in the geographic science community and made it possible for geography to establish its own theoretical system and develop from the previous individual fragmented explanation of phenomena to a global scientific theoretical thinking. The endless resources distributed globally became reachable, accessible, and tradable, stimulating the rapid arrival of the industrial revolution, which in turn triggered the evolutionary fission of society based on it. As this algorithm originates from the continuous human exploration of the sea and geo-limits in the stage of geographic discovery, the multiple heterogeneous data comes from maritime archives, personal documents, nautical maps and route data, and the images, information and data are effectively integrated into the evolutionary logic through the organization and classification in the framework of the fleet algorithm.

The study selects the exploration route paths and logbook records of famous seafaring explorers such as Gil-Ean, Columbus, Vasco da Gama, Magellan, Cook, etc., combines the departure points, ports, islands, landing points, and exploration points recorded in the literature at that time to build the foundation, completes the foundation alignment against the trade ship data recorded by maritime agencies, and completes the algorithm test. From the observation of core data and the analysis of algorithmic data, it can be found that the collection of geo-data has not only brought great changes to geographic science, but also can clearly cognize 1) the new concept of geo-data and the order of acquisition; 2) the effective acquisition and full use of geo-data has given birth to the comparative study and inductive method in the era of philosophy of science; 3) the unified and standardized processing of data has promoted changes in the series of subject branches of geography and cartography.

In particular, it is necessary to point out that the study of the optimization of the path of the flotilla to explore the unknown territory, its significance is not limited to the discussion of historical geoscience, the logic of its occurrence and optimization behavior, the evolutionary laws of natural and social sciences of all human societies have homologous significance behind the impetus to social computing.

The exploration of the American voyages by Western colonists was accompanied by the mapping of the Caribbean. The Dutch, as the "coachmen of the sea" in the 17th century, also occupied an important place in the history of modern maps, especially with the publication of commercial maps. The Netherlands had become the center of Europe at that time.

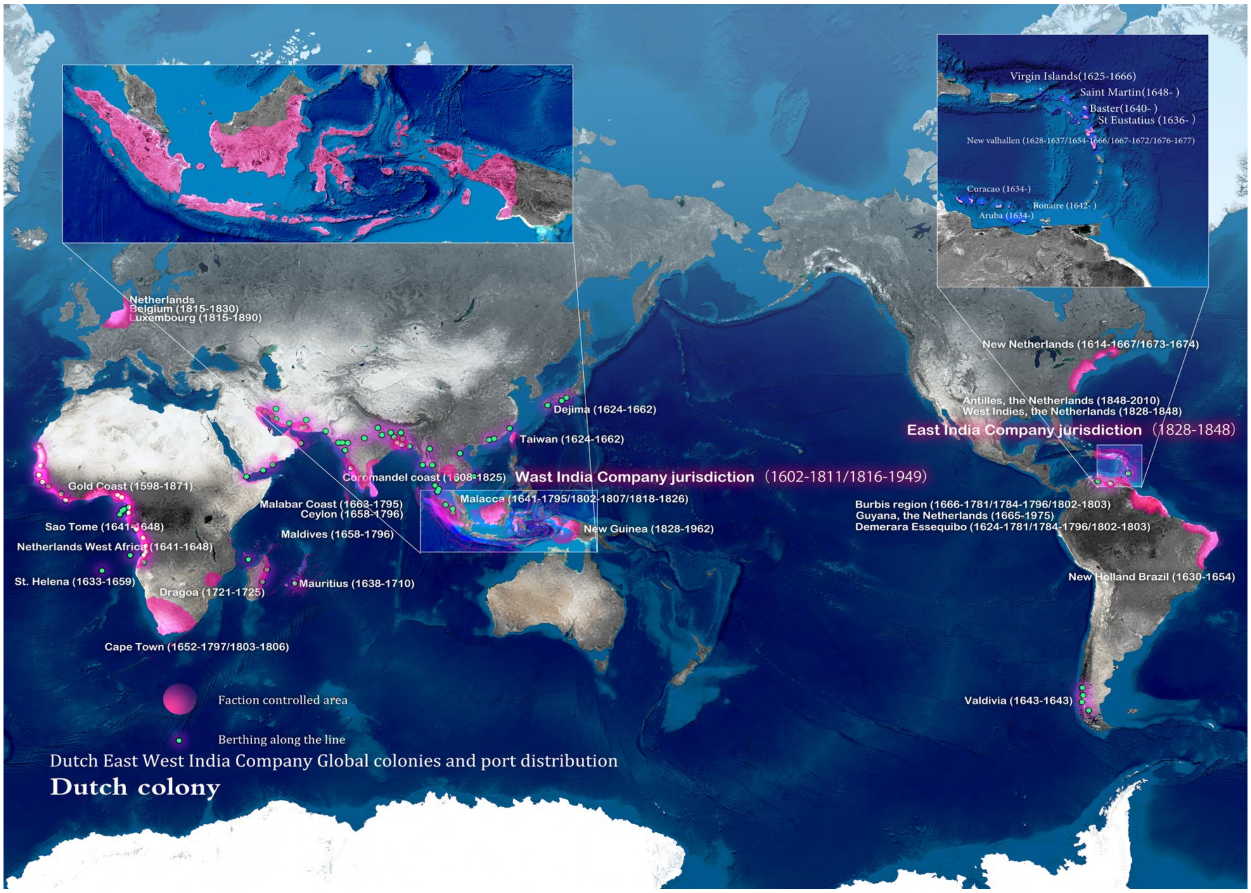

Fig. 2. Global colonies and port distribution of Dutch East West India Company

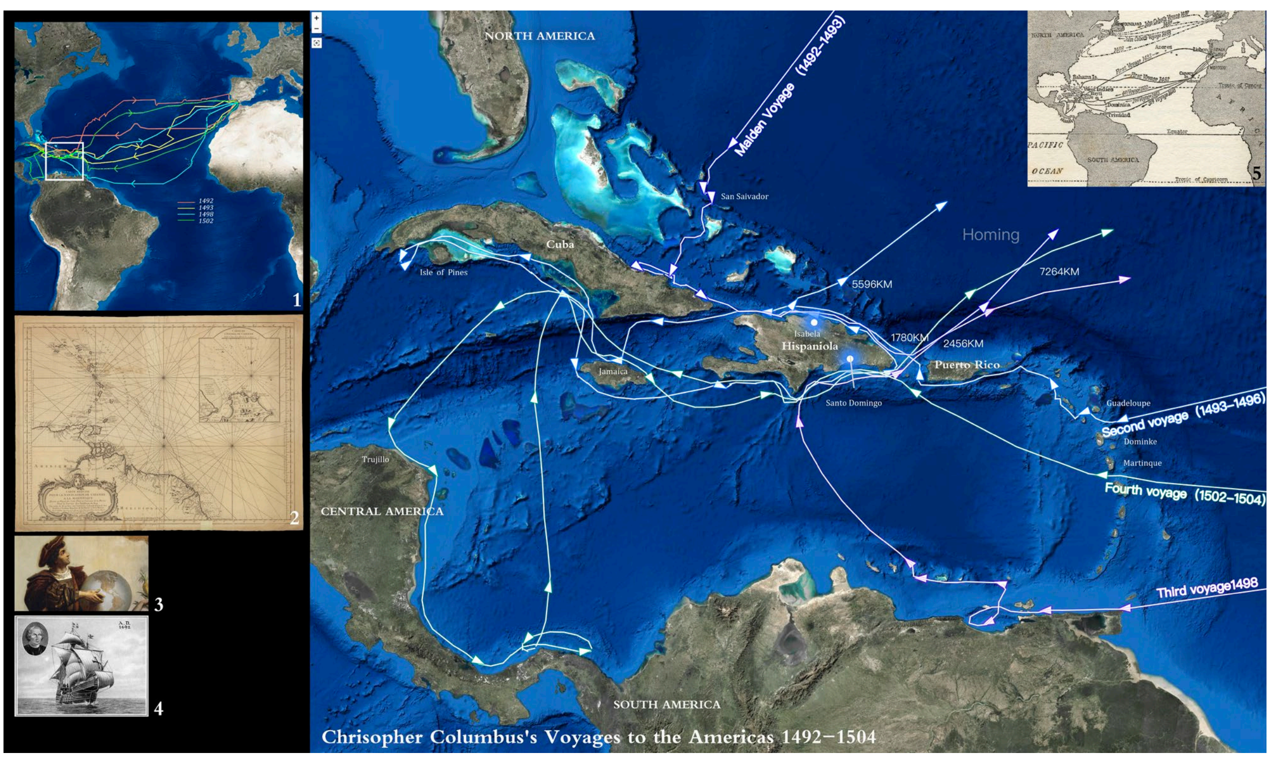

Fig. 3. Christopher Columbus's voyages to the Americas (1492-1504)

Cartographers and map publishers in the lowland countries, such as Gerardus Mercator, Abraham Ortelius, the Hondius family and the Blaeu family, published diverse and beautiful maps, atlases and globes. Geographic knowledge and trade expansion through the success on commercial maps can reflect the real achievements of the fleet's exploration. The National Library and National Archives of the Netherlands has created the Atlas of Mutual Heritage digital platform, and the library of the Macau University of Science and Technology has created the Global The National Library of the Netherlands and the National Archives have established the Atlas of Mutual Heritage digital platform, and the library of the Macau University of Science and Technology has established the Global Mapping of Macao digital platform, which provides a large number of digital images of maps.

The map images of the above institutions provide the main object of study for this paper. This paper chooses to study manuscript charts of the Caribbean region drawn by the Dutch West India Company in the mid-17th century, typical of European collecting institutions: 1. The route maps represented by Columbus are selected from various studies; 2. The dates and key islands, ports and garrisons are extracted in conjunction with literature such as logbook studies; 3. The typical geographical coordinates and routes are implemented through analysis and comparison of the extracted data The data are revised. It can be found that the map-making activity supported by the geo-exploration behavior of the fleet has a relationship structure that develops in parallel between the logbook manuscripts, cartographic standards and printed products, each with its own focus.

Anyone familiar with the maps of American exploration made by the Spanish and Portuguese in the 15th and early 16th centuries will note that the accuracy of the maps increased dramatically with the continued navigation of the fleet: whether it was the course of the coastline, the shape of the islands, or the relative position of the islands to the mainland and between the islands, there was no strong intuitive contradiction with modern maps, and therefore it was a strong evidence of the fleet's geographic knowledge-gathering behavior. The Dutch map improvements Among the improvements made by the Dutch, the following two cases are particularly notable: when compared with the Dutch East India Company (VOC) cartographer's representation of the South China Sea, the following features are present: 1) the style of the portolan charts is followed. 2) the data is recorded with much greater accuracy than the Portuguese maps of the 16th century. (3) The ship tracks and bathymetric data on some of the maps show that the hydrographic surveys were completed one after another by the fleet traveling in the subsequent routes. 4) The Dutch cartographers generally drew shoals on the edges of the islands and the land edges, which can prove the depth of ground observation during the fleet's multiple stops. smaller, shallower-draft vessels were involved to accomplish the task of actively surveying riverbanks.6) Reconnaissance of the coastal zone, mapping of the interior, and expeditions for the needs of the agricultural colonial economy all required military support and deterrence. The management of colonial settlers and aborigines required religious paralysis and accommodation, and the appearance of forts, churches, cemeteries, and plantations in the maps also attest to the great advances in geographic knowledge made by the Dutch West India Company as it expanded its trade network in South America. The development of geographic knowledge and trade needs also accompanied the development of colonial expansion.

V. Conclusions and Future Work

For how to explore the unknown foggy domain in the process of common knowledge evolution, this paper constructs a multi-objective dynamic search and achieves dynamic optimization and knowledge discovery by a series of associated algorithms that apply evolutionary computation to an uncertain environment. The main achievements of this paper are: i. a fleet algorithm based on multi-objective dynamic optimization in the misty domain is proposed; ii. an incentive evolution mechanism with exploration goals is proposed to build a model by constraining fleet exploration rules, dynamic path planning combined with behavioral goals of port acquisition data and distributed data exchange and sharing; iii. an adaptive method is used to update the geo-data carried and distributed by the fleet to obtain the global voyage to achieve The optimal path for solving the dynamic planning of data.

The algorithm addresses the continuous space-time optimization problem by introducing the solution memory (port) as the geo-data model and applying the dynamic adaptive feedback adjustment strategy to dynamically adjust the port attractiveness size to improve the model's ability to solve the social computing problem. Focusing on the improvement of the initialization method for geo-data acquisition, significant improvements in the ability to produce global sensing and local event derivation for early geo-knowledge production can be achieved, with faster convergence, enhanced global search capability, and improved solution accuracy.

The shortcoming is that, while corroborating the ecology of early global geo-knowledge production, the fleet algorithm still needs to evolve due to the complexity of the global geographic discovery with a large multi-objective scale. Efforts are made to improve robustness and evolutionary service to social evolutionary computation by adding complexity levels.

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