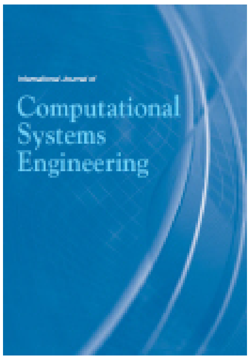

International Journal of Computational Systems Engineering

ISSN online: 2046-3405 - ISSN print: 2046-3391
https://www.inderscience.com/ijcsyse

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DOI: 10.1504/IJCSYSE.2022.10055659

Article History:

Received:	16 November 2022
Last revised:	07 February 2023
Accepted:	09 March 2023
Published online:	19 March 2024

A study on the application of teaching differential equations in higher mathematics based on visual network topology algorithm

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Abstract: The effect of teaching evaluation of differential equations in higher mathematics involving network visualisation is extremely advantageous in a multidimensional evaluation system. The study compares the teaching idea of higher mathematical differential equations to a signal flow diagram in a network topology, with mathematical variables as branch nodes for visual structural presentation. A force-guided layout algorithm is introduced to avoid crossover and overlap of nodes. A grey wolf optimisation algorithm incorporating dynamic weights is also used to prioritise the mathematical calculations in conjunction with the features of mathematical differential teaching. The results of the algorithm performance tests showed that the IGWO-visualised layout algorithm had the best optimisation of the functions, with an average optimisation time of 1.6874 s, while the force-guided layout algorithm had an average optimisation time of 12.5986 s.

Keywords: visual networks; force-guided layout algorithms; IGWO; teaching; topology.

Reference to this paper should be made as follows: Li, L. (2024) 'A study on the application of teaching differential equations in higher mathematics based on visual network topology algorithm', *Int. J. Computational Systems Engineering*, Vol. 8, Nos. 1/2, pp.87–95.

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1 Introduction

The rise of visualisation technology is driving innovative developments in computer networking technology. Visualisation technology is an interface technology for data, algorithms and processing that improves the ability to identify abstract data (Ding and Zhuang, 2018; Hao et al., 2018). Network topology is a topological relationship created by interconnecting network devices, and visualisation can abstract this connection to a topological relationship on a computer. Input control and data storage are visualised using visualisation software techniques and programming languages, and signal data processing is carried out in modules within the software, such as the main control interface and visual graphical editor, to visualise the teaching of mathematical differential equations (Ivanova, 2019; Qi et al., 2019). The goal of network visualisation is to present network data graphically to the user, to aid understanding of the structure and relationships within the network data, and to uncover valuable information hidden within the network data. Current research on network visualisation has focused on automatic node layout techniques and visualisation system design for single-layer networks. Due to the logical and coherent nature of teaching differential equations, the research uses an improved visualisation network algorithm to prioritise the teaching of mathematical differentials to ensure that students have a better understanding of how mathematical variables are computed in relation to each other. Through the above research design, the study expects to help students understand abstract relationships in mathematics in an intuitive and visual way, and achieve a more comprehensive and in-depth grasp of the content of differential equations in higher mathematics. The research assumes that the application of visual network topology algorithm to the teaching evaluation of differential equation of higher mathematics has ideal effect, and the teaching evaluator who completes differential equation of higher mathematics in a more intuitive form is also the purpose and goal of the research. The innovation points of the research are as follows.

1 The traditional force guided placement algorithm is improved to overcome the disadvantage that it is not suitable for social network structure analysis and display.

2 Based on the visualisation of network topology, the evaluation of differential equation teaching in higher mathematics is realised with the help of grey wolf optimisation algorithm.

3 Setup comparative datasets and algorithms to verify the application effect of the methods in the teaching of differential equations in higher mathematics.

Section 2 of the research analyses the research status of the visualisation network topology algorithm and the teaching of differential equations in higher mathematics. Section 3 focuses on the visualisation network topology under the force guided layout algorithm and the application of the visualisation network topology algorithm in the teaching of differential equations in higher mathematics. Section 4 analyses the application effect of the visualisation network topology algorithm. Section 5 summarises the experimental results and points out the existing problems.

2 Related works

To alleviate students' emotional stress when learning higher mathematics, Vorontsova and Chebun'Kina (2021) identified the most difficult topics in the unit of study by analysing the emotional responses of students when learning higher mathematics as recorded in a colour matrix, which led to strategies for improving the teaching format. Innovative teaching aids are another way for educators to deliver the curriculum to students; researchers such as Zakaria integrated a formal computer algebra system into the teaching of differential equations to provide experiential lessons for mathematics students, and this innovative way of teaching differential equations was well received by students, helping them to better understand conceptual knowledge (Zakaria et al., 2019). The contemporary trend in education is to transition from traditional face-to-face teaching to blended learning, where new online tools are introduced into the educational process. Semakin (2020) proposed to create two balanced components of the educational process in blended learning by combining traditional classroom teaching elements with online learning elements to find the best way to organise the learning process in higher mathematics. The results of the study showed that students have higher learning initiative in a course on integration of differential equations in a blended mode of teaching. The mathematical modelling approach is crucial to the scientific approach to the study of physical processes and phenomena because of the scientific and cognitive potential and versatility of mathematical models. Kornilov (2019) scientist provides a scientific view to promote students' understanding of mathematical modelling and differential equation theory. Research has shown that in practical lessons on differential equations, students effectively acquire the ability and skills to find solutions to inverse problems mathematically. To solve the boundary value problem of higher order volterra integro-differential equations, Dawood et al. (2020) proposed to solve the problem by the variable iteration method and modified homotopy perturbation method, and the results showed that the variable iteration method has high accuracy in solving volterra integro-differential equations.

Topology control is an effective method to improve the energy efficiency and fault tolerance of wireless sensor networks and thus extend the network lifetime, Wang et al. (2018) proposed a topology control algorithm for wireless sensor networks based on fault-tolerant dual cluster heads to achieve network lifetime extension and improve fault tolerance, and simulation results show that compared with traditional clustering algorithms, wireless sensor network topology control algorithms can reduce power consumption, extend network lifetime and improve fault tolerance. In order to solve the problem of low acceptance rate and low cost-effectiveness caused by existing virtual network embedding algorithms ignoring the topological characteristics of nodes, Liu et al. (2018) introduced the field theory of physics into virtual network embedding and proposed a topological potential-based virtual network embedding algorithm, and the experimental results showed that compared with existing virtual network embedding algorithms, the system has a higher acceptance rate under simulated conditions rate and good cost performance ratio. Zhang et al. (2018) proposed a new method to accelerate the identification of network topology, which uses a node-branch correlation matrix to represent the basic network topology and achieve a dynamic network topology. Clusterisation is considered as one of the most important energy-efficient solutions in wireless sensor networks, but poor cluster head selection may consume more energy than other sensor nodes due to packet transmission between cluster members and aggregated nodes. Sekaran et al. (2020) proposed a new cluster head selection method using the grey wolf optimisation algorithm and developed objective functions and weight parameters for efficient cluster head selection and clustering, compared to the algorithm proposed in the study outperformed other algorithms in achieving better network performance. The grey wolf optimisation algorithm is a metaheuristic algorithm inspired by the social hierarchy and hunting behaviour of the grey wolf. To solve the beamforming problem of smart antennas in code division multiple access systems, Mohsin et al. (2020) used the grey wolf optimisation algorithm on a uniform linear antenna array to obtain the optimal beam steering map to reduce some of the peaks in the sound pressure level, and simulation results showed that the grey wolf optimisation algorithm-based approach could achieve faster convergence and higher beamforming accuracy compared to genetic algorithms. Typical grey wolf optimisation algorithms are more suited to development than exploration and still fall short in terms of site update formulations. Inspired by differential evolution and particle swarm optimisation algorithms, Long et al. (2019) improved the exploration capabilities of the grey wolf optimisation algorithm by using the best information about individuals and randomly selected individuals, and simulations showed that the algorithm outperformed the basic grey wolf optimisation algorithm in most cases with the same or less evaluation of the maximum fit function.

The research results of scholars at home and abroad show that many scholars mainly focus on the teaching effect of differential equations and solving the mathematical problems of differential equations, but less attention is paid to the research of visualisation algorithms as a teaching tool for differential equations. The visual network topology algorithm can visualise the relationships between abstract data, and the grey wolf optimisation algorithm can prioritise the content, and the combination of the above literature shows that both algorithms have a wide range of applications and rich research results. Based on this, the study proposes to use the visual network topology algorithm to assist in the teaching of differential equations, and to use the grey wolf optimisation algorithm to prioritise the teaching content.

3 Application of visual network topology algorithms to mathematical differential equations

3.1 Visualisation of network topology under force-guided layout algorithms

Network topology refers to a topological relationship formed by the connection between network devices, and visualisation is to abstract this connection into a topological relationship on the computer. The task of network topology visualisation is to show this topological relationship in a visual way, in order to facilitate managers to intuitively understand this topology more intuitively (Han, 2020). The development of visualisation technology plays a crucial role in driving the development of computer networks, and is gradually becoming an interface technology between data, algorithms and processing to enhance people's perception of abstract data. The visualisation of network topology algorithms is the study of network topology relationships formed by the construction of vertices and edges of graphs, and they can be used to solve system optimisation problems in simulation models by adding a visual programming language to them to achieve a simulation presentation of their algorithms. The transfer function plays an important role in the analysis of network systems, where the system is referred to given external action conditions and parameters. Here the complex time-domain model of the system is transformed into a simple frequency-domain model by using mathematical variations, i.e., using the linear orthogonal Laplace transform, whose formula is shown in equation (1).

$$F(s) = \int_0^{\infty} f(t)e^{-st}dt \tag{1}$$

In equation (1), $f(t)$ is the time function, $F(s)$ is the mapped function, t is the time and s is the product operator in the complex time domain. The total system of two tandem systems is represented as a product of transfer functions to achieve a decomposition of the system. The Shannon-Happ formula is also used to simulate and process the computer language. The core idea of the formula is to determine whether the signal flow diagram is switched on or off to distinguish between open and closed signal flow diagrams, in which the branch loops are in contact with each other and their loop gains are relatively independent, so the transfer function of the system is to some extent consistent with the loop gain of the signal flow diagram with consistency, the results of the calculation method are expressed in equation (2).

$$\begin{aligned} &G(s) = B(s)/A(s) \\ &\rightarrow A(s) - B(s)^*/G(s) = 0 \end{aligned} \tag{2}$$

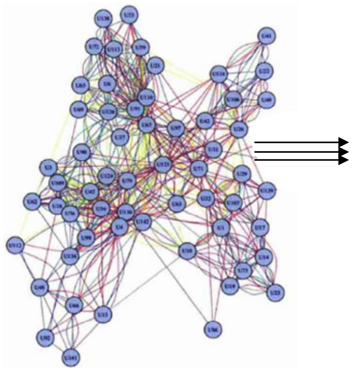
In equation (2), $G(s)$ is the transfer function and $B(s)$, $A(s)$ is the system input and output quantities respectively. At the same time the mathematical differential equation because of the diversity of its system variables, so the nodes in the signal flow diagram to represent the variable, with a directional branch to connect up the nodes, and set the branch gain on behalf of the variable coefficients, to establish the signal flow diagram of its system. For the one-way system, the input and output of its system represent a receipt point respectively, that is, with the help of the linear additivity of the transfer function, to achieve the value of each variable node and gain in the differential equation, the final output of the system can be expressed as shown in equation (3).

$$Y(s) = Y_1(s) + Y_2(s) + Y_3(s) + \ldots + Y_n(s) \tag{3}$$

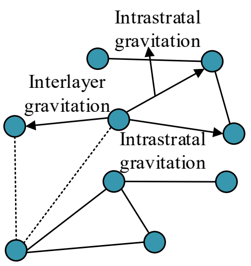
In equation (3), n is the number of input systems and $Y(s)$ is the total system. The topology algorithm allows for algorithmic splitting of differential equations and differentiates the stepwise nature of algorithmic computation and mathematical teaching with loop intersections. Figure 1 shows a flowchart of the network topology algorithm.

The structure of the algorithm in Figure 1 shows that a good representation of the digital teaching content in a topological structure makes all parts of the content connected, and this data is imported into an array to calculate the loop branches and the combined gain in order to obtain the combined form of mathematical teaching, and subsequently to judge whether there are intersections in the loop connected by each node and branch, i.e., to obtain the combined form of mathematical teaching at the end. Simultaneous layout algorithms are an important method for visualising network topologies. It is a choice made in combination with the visualisation requirements and the type of network, recalculating the points and edges in the topology in order to rationalise its structure and reduce the intersection of node connections. The logical layout algorithm has a wide range of applications, including numerical layout, ray layout, hierarchical layout and force-guided layout. The force-guided layout algorithm is mainly based on the physical idea of layout inspection, which can effectively take into account the positive and negative forces between node connections, i.e., nodes are constantly adjusted and changed under these two forces to achieve a balanced state of nodes, reducing crossover and overlap in the topology. This reduces crossover and overlap in the topology, resulting in a more uniform and coordinated distribution of nodes and a better layout effect. The force-guided layout algorithm is the mainstream layout algorithm in the field of social network information visualisation, and the simulation of the algorithm can be carried out after ensuring that the distance between connected nodes is suitable within a certain range. Figure 2 shows a schematic diagram of the network topology and the node stress structure.

Figure 1 Program flowchart of network topology algorithm, (a) node connection diagram schematic diagram of node layer gravity distribution (b) node connection diagram schematic diagram of node layer gravity distribution (see online version for colours)



(a)



(b)

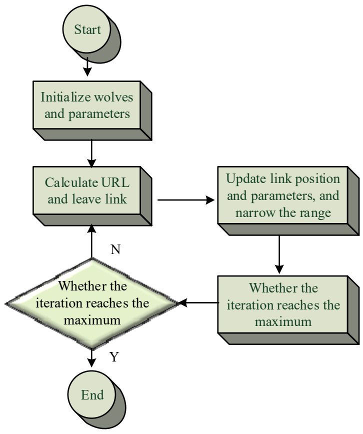
However, the force-guided layout algorithm is unable to identify the node structure and paths due to the proximity of the nodes, and thus cannot grasp the logical relationships under the deeper levels of the nodes. Therefore, based on this, the Subgroup analysis layout (SAL) algorithm is introduced to perform subgroup analysis on the node information in the network topology (Mansouri and Bouhlel, 2019). Subgroup analysis can help participants to better understand the characteristics of the network structure and can effectively improve the force-guided layout algorithm with the help of role analysis and key attribute analysis. Subclustering by key attributes is used to determine whether two indicator variables belong to the same subcluster and to calculate the statistical probability of correlation.

The formula for calculating the statistical probability that a single variable should belong to the same subgroup is shown in equation (4).

$$BS = \max_{m=1}^{\delta} q_m f_m \tag{4}$$

In equation (4), BS is the statistical probability that a single indicator i belongs to the j subgroup, q_m is the correlation between the m same-attribute matrix and the same-subgroup matrix, and f_m is the degree of similarity between a single indicator i and the j subgroup on the m attribute.

Figure 2 Network topology diagram and node stress structure diagram (see online version for colours)



3.2 *Application of visual layout algorithms in teaching mathematical differentiation*

The application of visual network topology to mathematics teaching means that the input checking and saving of data is achieved with the help of visual software technology and programming languages, and the processing of signal data is achieved with modules such as the master control interface, visual graphical editing and simulation data generator in the software. While mathematical differential equations are the main research content in the teaching design, their visualisation makes it difficult for students to achieve a good grasp of the learning content. Therefore, the study is based on this, through the introduction of the grey wolf optimisation algorithm to achieve priority selection in the teaching of mathematical differentiation, to ensure that students can better have a clearer content of how to calculate between mathematical variables, more conducive to the development of mathematical teaching activities (Татьяна Анатольевна Бродская, 2019; Qamar et al., 2018; Muzhikova, 2018). The grey wolf optimisation algorithm simulates the predatory behaviour of the grey wolf to obtain the target characteristics, i.e., by calculating the fitness of individuals and sorting the top three 'wolves', and then updating the position and parameters of the bottom 'wolves' to achieve the maximum number of iterations of the target. The maximum number of iterations to achieve the goal is reached. However, the grey wolf optimisation algorithm is prone to slow convergence at a later stage, so the study implements improvements to the algorithm by adding convergence factors and dynamic weights to avoid falling into local optimum behaviour. The formula is shown in equation (5).

$$X(t+1) = X_p(t) - A * D$$
$$A = 2a * r - a \quad (5)$$

In equation (5), D is the distance between the grey wolf and the target value, X_p is the location of the target value, t is the number of iterations of the algorithm, X is the location of the grey wolf, r is a random number in the range (0–1), is the convergence factor, aA is the range control parameter, and the absolute value of A is greater than 1 for global search and vice versa for local search. The convergence factor in the original algorithm is linearly decreasing, which makes it difficult to adapt the algorithm to changes in all parameter values. Therefore, the study designs an improved convergence factor to make the grey wolf optimisation algorithm better determine the population range and find the local optimum even if the number of iterations increases. The formula for the improved convergence factor is shown in equation (6).

$$a' = m - m\left(t/\max\right)^4 \quad (6)$$

In equation (6), max is the maximum number of iterations, m is the turning point of the number of iterations, which is mainly assigned with the specific algorithm settings, and a' is the improved factor parameter. The introduction of dynamic weights enables dynamic changes in wolf position updates and is an improved strategy for the iterative process to dynamically reduce the range to better update the position of individual grey wolves. The formula is shown in equation (7).

$$w_b = \|X_b\| / \left(\|X_1\| + \|X_2\| + \|X_3\|\right)$$
$$X_1 = \lambda_1 X_y - A_{a'} * D_y \quad (7)$$

In equation (7), w_b is the learning weight of the next ranked wolf in the top three, which varies with the number of iterations, y is the highest to lowest individual representative of the grey wolf population, b is the higher ranked wolf, and λ_1 is the parameter factor in the weight setting. The introduction of the improved grey wolf optimiser (IGWO) to the original visual network topology algorithm allows for a finite order filtering of the mathematical teaching topology to obtain a clearer idea of the data calculation steps. Figure 3 shows a schematic diagram of the mathematical data information extraction process under IGWO.

The calculation of mathematical differential equations and the design of teaching models cover a wide variety of content, and students' computational thinking is easily influenced by mathematical thinking and the parameters of complex equations, so it is necessary to iterate over the parameters of indicators of different priorities in order to filter the content of the data to fit the set of equations. Figure 4 shows the relationship between the mathematics teaching network topology in the visualisation software.

The main control interface in Figure 4 enables visualisation of graphical processing and system performance, i.e., the aggregation of data information by storing and analysing the results of this visualisation in the form of files and simulations. The extraction of mathematical features and the development of mathematical teaching models help students to better understand mathematical content.

Figure 3 Schematic diagram of mathematical data information extraction process under grey wolf optimisation algorithm (see online version for colours)

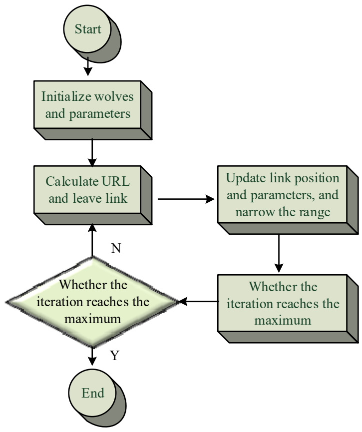
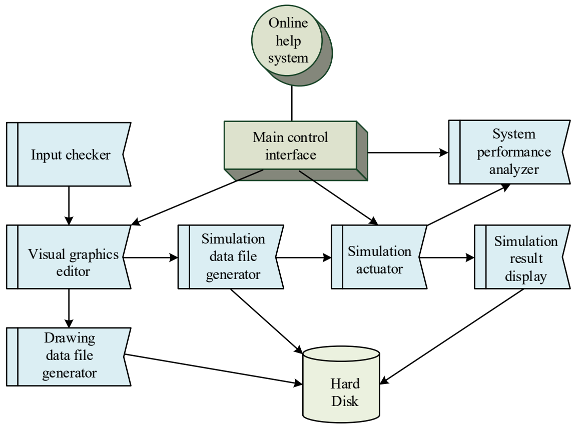


Figure 4 The application of mathematical teaching network topology in visualisation software (see online version for colours)



4 Analysis of the effectiveness of visual layout algorithms in teaching mathematical differentiation

To show the effect of the layout of the constructed network topology, the study was meant to have a maximum allowed number of evolutionary generations of 10,000 and to end the iteration when the error was less than or equal to 1e-3. The language in which the experiments were written was MATLAB 6.5 and the platform was a P42.0 PC computer. The datasets taken for the experiments are shown in Table 1 and include three datasets. Of these, dataset A and dataset B are real network data and dataset C is simulated data.

The experiments were run randomly five times to compare the average function value, minimum function value, average number of iterations, minimum number of iterations, and average optimisation time of the four topology algorithms: force-guided layout algorithm, SAL-force-guided layout algorithm, visualised layout algorithm, and IGWO-visualised layout algorithm. The results are shown in Table 2. The IGWO-visualised layout algorithm has the best optimisation of the function with an average optimisation time of 1.6874 s, while the force-guided layout algorithm has an average optimisation time of 12.5986 s. Although the functions find the global minima (0, 0) due to their strong oscillatory nature and the property that the global minima are surrounded by local minima, the IGWO-visualised layout algorithm all finds the global minima (0, 0). The good results of the IGWO-visualised layout algorithm may be due to having a tight neighbourhood topology, while the force-guided layout algorithm is less effective, possibly due to being a more complex network topology.

Table 1 The dataset used in the experiment

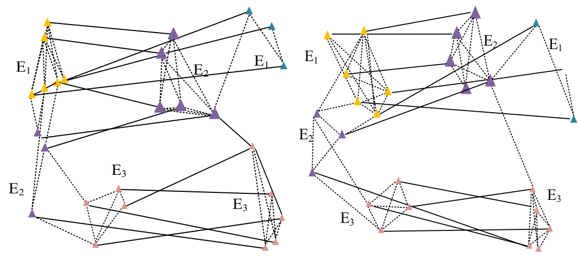
Dataset	*Dataset A*	*Dataset B*	*Dataset C*
Type	Krackhardt-High-Tech	Vickrs-Chan-7th graders	Analogue data
Number of layers	3	2	2
Number of nodes	21	29	13
Number of edges in layer	206	292	53
Number of interlayer edges	113	29	13

Table 2 Performance of the five NTPSOs on Schaffer'f6

Topology	*Minimum number of iterations*	*Average optimisation time (s)*	*Average value*	*Average number of iterations*	*Optimal value*
Force directed layout algorithm	201	12.5986	0.0055	5943.4	0
Sal force guided placement algorithm	303	6.8146	3.2104 e-4	2021.8	0
Visual layout algorithm	284	5.6646	6.3863 e-4	2021.8	0
IGWO visual layout algorithm	220	6.1646	9.8214 e-4	2211.5	0

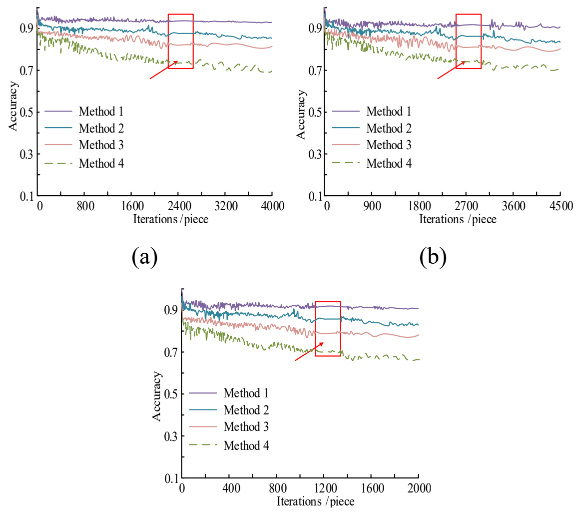
Setting the same gravitational parameters and repulsive forces, the experiments were conducted to analyse the visual layout results with dataset C as an example due to space limitation. Figures 5(a) and 5(b) represent the visual layout results of the visual layout algorithm, IGWO-visualised layout algorithm, respectively. The letter E in the figure refers to the different communities and the triangles refer to the different nodes. Overall, both visual layout algorithms have two characteristics of uniform node distribution and more significant correspondence between nodes and replicas. However, the nodes of the IGWO-visualisation layout algorithm are subject to inter-layer gravity, which causes the nodes within a community to move closer to the centre of the community. In addition, the nodes of the IGWO-visual layout algorithm are subject to interlayer gravity, which corresponds to a smaller node offset.

Figure 5 Visual layout effects of two visual layout algorithms, (a) visual layout algorithm (b) IGWO visual layout algorithm (see online version for colours)



(a) (b)

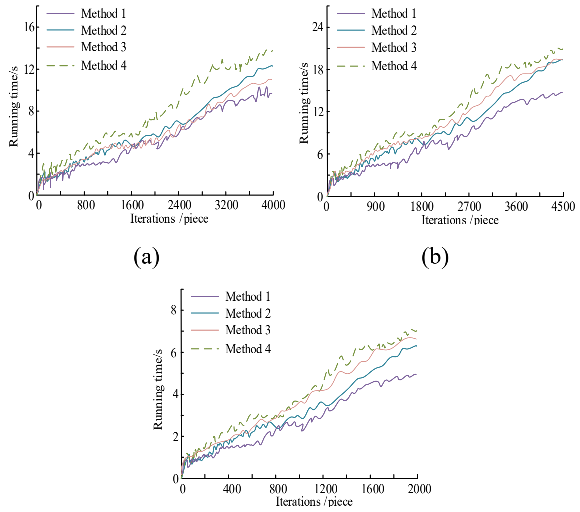
Figure 6 Comparison of accuracy under three datasets A–C, (a) comparison of accuracy of dataset A (b) comparison of accuracy of dataset B (c) comparison of accuracy of dataset C (see online version for colours)



(c)

To further analyse the performance of the layout algorithm for IGWO-visualisation (method I), the study validated it against three comparative algorithms, namely the ZigBee network topology visualisation reproduction algorithm, the visualisation topology algorithm for co-word networks, and the new intelligent visualisation algorithm for distribution networks with multiple data elements, which are represented by methods II–IV respectively. Figures 6(a), 6(b) and 6(c) refer to the comparison of accuracy rates under the three datasets A–C, respectively. Under the three datasets, all four visual network topology algorithms converge in approximately the same number of iterations, with 2,400, 2,700 and 1,200 iterations under the three datasets A–C, respectively; and the IGWO-visual layout algorithm has the highest accuracy rate, with 95.6%, 93.6% and 92.1% under the three datasets A–C, respectively. The accuracy of the remaining three visual layout algorithms had a wide range of values, with the ZigBee network topology visualisation reproduction algorithm having the second highest performance and the new distribution network intelligent visualisation algorithm with multiple data elements having the weakest performance.

Figure 7 Comparison of running time under three datasets A–C, (a) comparison of running time of dataset A (b) comparison of running time of dataset B (c) comparison of running time of dataset C (see online version for colours)



(a) (b)

(c)

Figures 7(a), 7(b) and 7(c) refer to the comparison of the running times under the three datasets A–C, respectively. In dataset A, the maximum running times of the layout algorithm for IGWO-visualisation, the topology visualisation reproduction algorithm for ZigBee networks, the visualisation topology structure algorithm for co-word networks, and the new intelligent visualisation algorithm for distribution networks with multiple data elements are 8.26 s, 9.12 s, 12.13 s, and 13.25 s, respectively; in dataset B, the four visualisation network topology algorithms have maximum In dataset B, the maximum running times of the four visual network topology algorithms were 14.56 s, 19.03 s and 20.39 s respectively; in dataset C, the maximum running times were 4.65 s, 5.92 s, 6.12 s and 6.87 s respectively; in the three datasets, the four visual network topology algorithms had approximately the same variation pattern under different numbers of iterations, and the maximum numbers of iterations in the three datasets A–C were The maximum number of iterations in the three datasets A–C are 4,000, 4,500 and 2,000 respectively, when the corresponding running time of the four visual network topology algorithms is maximum.

The study applied the proposed visual network topology algorithm to the evaluation of mathematical differential teaching, setting the teaching cases as 1,000, the teaching rating as 0–100, and the teaching effectiveness rating as low, medium and high, with the corresponding ratings as below 30, [30, 70] and over 70. Figure 8 refers to the effectiveness of the proposed visual network topology algorithm in the teaching of mathematical differentiation. As can be seen from the figure, the number of cases with teaching effectiveness ratings of low, medium and high was 214, 321 and 465 respectively out of 1,000 teaching cases, with an average mathematical differential teaching rating of (68.56 ± 8.36). Thus, the majority of cases had high teaching ratings.

Figure 8 Application effect of visual network topology algorithm in mathematics differential teaching (see online version for colours)

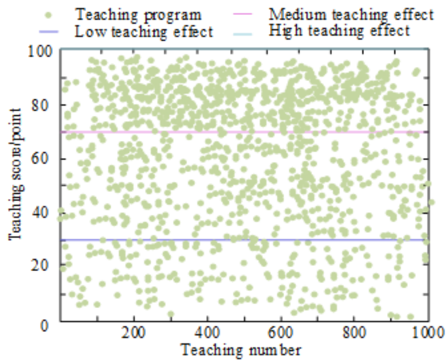
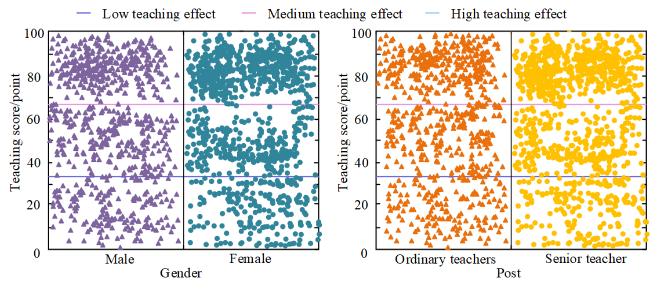


Figure 9(a) refers to the teaching ratings of mathematics calculus teachers by gender. As can be seen from Figure 9(a), male mathematics calculus teachers were better evaluated in teaching compared to female teachers, with an average teaching rating of (71.23 ± 7.63) and (65.26 ± 6.98) for both male and female mathematics calculus teachers. Figure 9(b) shows the teaching ratings of the different positions of Mathematics Calculus teachers. Senior teachers had better teaching ratings compared to regular teachers, with mean teaching ratings of (65.23 ± 6.87) and (75.34 ± 7.26) for regular and senior mathematics calculus teachers.

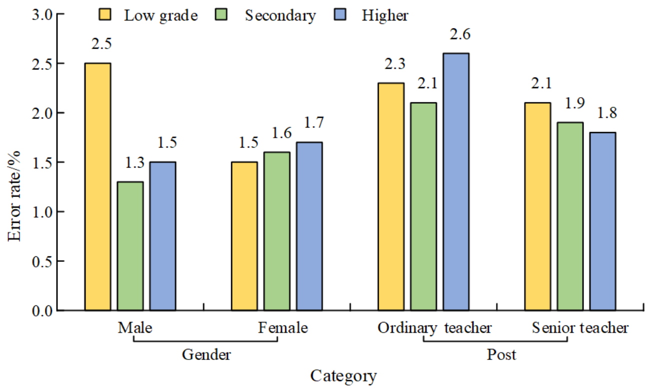
Figure 9 Teaching grades of mathematics differential teachers of different genders and positions (see online version for colours)



(a) (b)

The study compared the results obtained with the assessment results of the teaching experts. Figure 10 refers to the error rates for the different categories of teaching level evaluations. For gender, male mathematics calculus teachers had higher overall error rates than female teachers for the three teaching evaluations, with error rates of 5.3% and 4.8% respectively, and an overall error rate of 10.1%; for position, general mathematics calculus teachers had higher overall error rates than senior teachers for the three teaching evaluations, with error rates of 7.0% and 5.8% respectively, and an overall error rate of 12.8%.

Figure 10 Error rate of evaluation of different teaching levels (see online version for colours)



5 Conclusions

To address the problems of the traditional visual network topology algorithms in terms of low efficiency in fast layout, the study proposes an IGWO-visual layout algorithm and applies it to the teaching evaluation of differential equations in higher mathematics. The simulation results of the algorithm show that both visual layout algorithms have two characteristics of uniform node distribution and more obvious correspondence between nodes and copies. However, the IGWO-visual layout algorithm causes the nodes within the community to move closer to the centre of the community, and the corresponding node offset is smaller. 2,400, 2,700 and 1,200 times of convergence were achieved for the four visual network topology algorithms under the three datasets of A–C, respectively; and the IGWO-visual layout algorithm has the highest accuracy rate, with the accuracy rates under the three datasets of A–C being 95.6%, 93.6% and 93.6%, respectively were 95.6%, 93.6%, and 92.1%. The results of the teaching evaluations showed that male mathematics differential teachers had higher overall error rates than female teachers in the three teaching evaluations, with error rates of 5.3% and 4.8%, respectively, and mean teaching scores of (71.23 ± 7.63) and (65.26 ± 6.98); general mathematics differential teachers had higher overall error rates than senior teachers in the three teaching evaluations, with error rates of 7.0% and 5.8%, with mean teaching ratings of (65.23 ± 6.87) and (75.34 ± 7.26). The IGWO-visualised layout algorithm has good network layout capabilities and can evaluate the effectiveness of mathematical calculus teaching more accurately. However, the study still suffers from the following problems, the fast layout capability of the network node layer is weak and cannot be applied to large-scale network node layout.

Acknowledgements

The research is supported by: Teaching Reform Project of Yan'an University: The theory and practice on 'Internet + Education' (YDJGYB21-16).

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