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A Vector Line Simplification Algorithm Based on the Douglas–Peucker Algorithm, Monotonic Chains and Dichotomy

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Abstract: When using the traditional Douglas–Peucker (D–P) algorithm to simplify linear objects, it is easy to generate results containing self-intersecting errors, thus affecting the application of the D–P algorithm. To solve the problem of self-intersection, a new vector line simplification algorithm based on the D–P algorithm, monotonic chains and dichotomy, is proposed in this paper. First, the traditional D–P algorithm is used to simplify the original lines, and then the simplified lines are divided into several monotonic chains. Second, the dichotomy is used to search the intersection positions of monotonic chains effectively, and intersecting monotonic chains are processed, thus solving the self-intersection problems. Two groups of experimental data are selected based on large data sets. Results demonstrate that the proposed experimental method has advantages in algorithmic efficiency and accuracy when compared to the D–P algorithm and the Star-shaped algorithm.

Keywords: Line Simplification; Douglas-Peucker Algorithm; Monotonic Chain; Dichotomy

1. Introduction

With the development of remote-sensing technology, sensor technology, and Web 2.0, the large amounts of obtained spatial vector data produce great challenges in data storage, processing, and transmission. To enhance the processing capability for massive spatial vector data, new vector data simplification algorithms with high efficiency and robustness are urgently needed.

There are many classical methods used to simplify vector data, including the Douglas–Peucker algorithm (D–P algorithm) [1], Ramer algorithm [2], and other algorithms [3–9]. The D–P algorithm [1] and Ramer algorithm [2] use a given distance tolerance to determine which vertices on a line are to be eliminated or retained. Lang [3] used a perpendicular distance tolerance to filter data, but the method was too time consuming [1]. Based on a sequential set of five procedures, McMaster [4] presented a conceptual model to process linear digital data. This employed method used the perpendicular distance tolerance proposed by Lang [4] to simplify the lines and used smoothing techniques to produce the most aesthetically acceptable results. Based on selecting local minima and maxima, an algorithm for compressing digital contour data has been developed by Li [5]. The new algorithm was more efficient than the D–P algorithm, but the result remained the same as the D–P algorithm. Visvalingam and Whyatt [6] used the "effective area" to simplify the line features and discussed the influence of rounding errors on a version of the Ramer–Douglas–Peucker algorithm [1,2] for line simplification. To show how to make robust, precise, and reproducible geographic information systems

(GIS) algorithms, Ratschek et al. [7] proposed a robust version of the R-D–P algorithm. Based on recognizing line shapes and filtering them against cartographic rules, Wang and Muller [8] proposed a Bend Simplify algorithm. The bend simplify algorithm attempts to simulate manual line simplification by using cartographic rules, and it is typically used to simplify naturally occurring features such as lakes and stream channels [10]. Based on the Li–Openshaw algorithm [11], the D–P algorithm, and the orthogonal simplification method, Samsonov and Yakimova [12] proposed a methodology and generalization model for the geometric simplification of heterogeneous line datasets.

The line simplification results processed by the above algorithms consisted of a set of original polyline vertices with no "Steiner" points. Other researchers have applied the "Steiner points" [13] to simplify the linear features [14,15]. The concept of Steiner points originates from the discipline of computational geometry and is referred to as a point or a set of points that are introduced when solving a geometric optimization problem to improve upon solutions based only on the original set of points [13,16]. On the basis of the traditional D–P algorithm [1], Cromley [14] used "Steiner points" to simplify a line; the experimental results showed that the proposed method is computationally faster than the traditional D–P algorithm [1]. Based on the method proposed by Li and Openshaw [11], Raposo [15] presented a scale-specific cartographic line simplification algorithm by using a hexagonal tessellation instead of a square grid. The hexagonal quantization algorithm draws from sampling and map-resolution theory as well as the concept of vertex clustering from computer graphics to yield a method which is simple and effective.

The experimental results addressed in the line simplification algorithms above show that good results have been achieved for each method and have been successfully applied to the corresponding fields. This has to be due to all the advantages concerning the D–P algorithm—it is highly effective at preserving the shape of the line, unique in vector curve compression at the presence of the threshold values and, above all, precise in a higher position, which is thereby often used to simplify lines [16,17]. However, the D–P algorithm is found to be flawed in that a large area deviation might be caused [18]. In addition, the method only addresses the curves themselves rather than the topological relations of the curves, thus leading to self-intersection problems [19]. Therefore, many scholars have improved the D–P algorithm in order to solve these self-intersection problems. A hierarchical representation scheme for planar curves was proposed by Ho and Kim [20], which used natural approximation and efficient localization. It was effective in removing self-intersections in all possible approximations for a curve using the cross-link technique, reducing computation time remarkably. Mantler and Snoeyink [21] introduced a new algorithm. They defined a notion of safe sets, which are fragments of linear features that can be simplified without introducing intersections or topology changes. This algorithm can also help to identify a collection of safe sets using the Voronoi diagram of points, but it is required to produce a Voronoi diagram, the efficiency of the algorithm is limited. To solve the self-intersection problems, Avelar and Müller [22] proposed an algorithm to compute the topological relations when compressing the polyline features. In this algorithm, simple geometric operations are used and tested step-by-step to check whether the topological relations have changed after compression. If the topological relations are not changed, the algorithm will terminate; otherwise, the topological relations will be maintained. Wu and Marquez [23] proposed a star-shaped algorithm (ST algorithm) to simplify the curves. The original curves are first scanned first and then divided into "Star" areas. Finally, the D–P algorithm is applied to compress the "Star" areas. The star-shaped algorithm solves the self-intersection problems, but it has the worst case $O(nm)$ time complexity, where n is the number of input vertices and m depends on the number of star-shaped regions, the time consumption and efficiency of this method is relatively high.

Most of the above improved D–P algorithms solved the self-intersection problems to simplify the linear objects; however, the algorithms used have the disadvantages of low efficiency and complex steps. To solve the self-intersection problems when using the D–P algorithm to simplify the linear objects and improve the efficiency of the algorithm, a new vector line simplification algorithm that combines the D–P algorithm, monotonic chains and dichotomy is proposed in this paper. There are

four main stages: first, the D–P algorithm is used to process the original lines; second, the monotonic chain method is used to divide the simplified lines into monotonic chains if the simplified lines have self-intersection problems; third, the dichotomy is used to quickly and accurately locate the self-intersection position of the simplified lines, process the self-intersection problems, and obtain the final result; finally, the experimental results are presented in this part, and the results of the experiments show that our proposed method demonstrates a more effective and higher performance.

The remainder of this paper is organized as follows. The basic theories, methods and steps of the new algorithm are introduced in Section 2. Experimental results and analysis are reported in Section 3. Conclusions are drawn in Section 4.

2. Methodology

In this section, we will first introduce the basic theories of the D–P algorithm, monotonic chains and the dichotomy method; then, the basic steps of the improved algorithm are introduced in further detail. A flow chart of the proposed research method is shown in Figure 1.

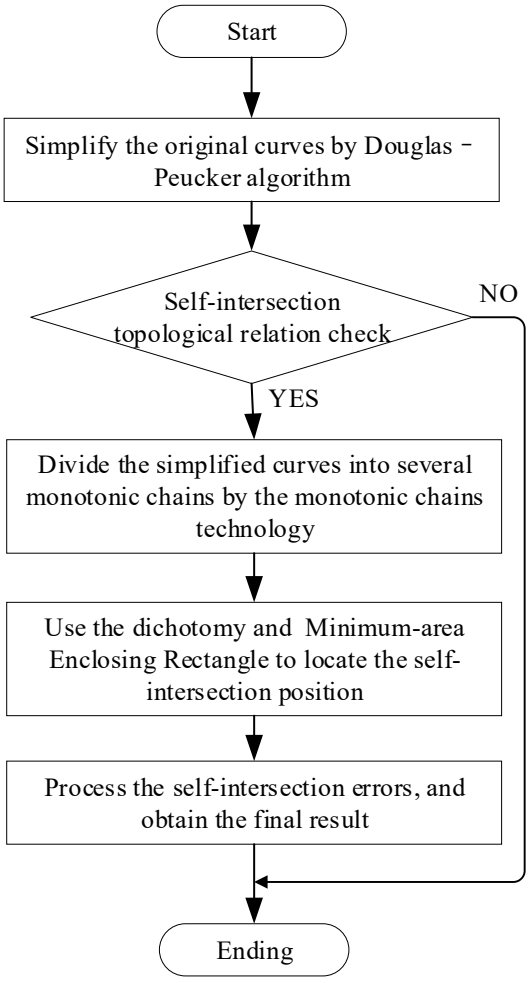


Figure 1. The flowchart of the proposed method.

2.1. Basic Theory of the Douglas–Peucker (D–P) Algorithm

The D–P algorithm is a classic algorithm used for curve compression. The algorithm is used to simplify polylines by deleting non-feature vertices and retaining the feature vertices. The basic theory and computational steps of the D–P algorithm are as follows [1,24]:

Step 1: For a curve L, which is composed of N coordinate vertices, the coordinate vertices set V is written as $V = \{v_1, v_2, \ldots, v_i, \ldots, v_N\}, (i = 1, 2, \ldots, N)$. First, connect the first vertex v_1 and the

last vertex v_N, to obtain a new straight line $L_{v_1v_N}$. Second, calculate the shortest distances between the remaining vertices $\{v_2, \ldots, v_{N-1}\}$ and the new straight line $L_{v_1v_N}$ and obtain the shortest distance sets $D = \{D_2, \ldots D_k, \ldots, D_{N-1}\}$ (D_k is the shortest distance between vertex v_k and the new straight line $L_{v_1v_N}$);

Step 2: Select the maximum distance ($D_{\max}$) with shortest distance D, $D_{\max} = D_k$ (D_k is the shortest distance between vertex v_k and the new straight line $L_{v_1v_N}$). Given a distance ε as the distance threshold, if $D_{\max} < \varepsilon$, then the remaining vertices $\{v_2, \ldots, v_{N-1}\}$ from vertices set $V = \{v_1, v_2, \ldots, v_N\}$ are deleted, the given curve L is compressed into a straight line $L_{v_1v_N}$ and the D–P algorithm is finished. If $D_{\max} \geq \varepsilon$, then the vertices set $V = \{v_1, v_2, \ldots, v_N\}$ is divided into two subsets V_t and V_s, that is, $V = V_t + V_s$ ($V_t = \{v_1, v_2, \ldots, v_k\}$, $V_s = \{v_k, v_{k+1}, \ldots, v_N\}$);

Step 3: For the subsets V_t and V_s, repeat step 1 and 2, respectively. If all of the calculated shortest distances are less than the giving distance threshold (ε), then end the D–P algorithm.

2.2. Monotonic Chains and Dichotomy

The theory of the monotonic chain is mainly derived from computational geometry [12,25]. For the curve L, the monotonic chain is defined as follows:

Monotonic chain: For a curve L, which is composed of M coordinate vertices, the coordinate vertices set V is expressed as $V = \{v_1, v_2, \ldots, v_i, \ldots, v_M\}, (i = 1, 2, \ldots, M)$; x_i is the X-axis coordinate of vertex v_i, and y_i is the Y-axis coordinate of vertex v_i. In the direction of the X-axis, for the coordinate vertices set $X = \{x_1, x_2, \ldots, x_i, \ldots, x_M\}, (i = 1, 2, \ldots, M)$, if $x_i \leq x_{i+1}$ $(i = 1, 2, \ldots, M)$ or $x_i > x_{i+1}$ $(i = 1, 2, \ldots, M)$, the curve L will be called a monotonic increasing (or decreasing) chain of the X-axis. Similarly, in the direction of the Y-axis, for the coordinate vertices set $Y = \{y_1, y_2, \ldots, y_i, \ldots, y_M\}, (i = 1, 2, \ldots, M)$ $(i = 1, 2, \ldots, M)$, if $y_i \leq y_{i+1}$ $(i = 1, 2, \ldots, M)$ or $y_i > y_{i+1}$ $(i = 1, 2, \ldots, M)$, the curve L will be called a monotonic increasing (or decreasing) chain of the Y-axis.

Dichotomy: Dichotomy is one of the most commonly used search algorithms for ordinal sequences and has a high search efficiency [12,13]. Given the target element t and the ordered sequence $K = \{k_1, k_2, \ldots, k_i, \ldots, k_U\}, (i = 1, 2, \ldots, U)$, $(t \in K)$, to search for the target element t from K, the basic theory of dichotomy is as follows:

Step 1: For the target element t, compare t with the intermediate element $k_{\frac{U}{2}}$ from the sequence K. If $t \neq k_{\frac{U}{2}}$, then K will be divided into two parts: K_1 and K_2, $K = K_1 \cup K_2$, $K_1 = \left\{k_1, k_2, \ldots, k_i, \ldots, k_{\frac{U}{2}}\right\}$ $(i = 1, 2, \ldots, U)$, $K_2 = \left\{k_{\frac{U}{2}}, k_{\frac{U}{2}+1}, \ldots, k_j, \ldots, k_U\right\} \left(j = \frac{U}{2}, \frac{U}{2} + 1, \ldots, U\right)$.

Step 2: For the target element t, if $t \geq k_{\frac{U}{2}}$, then execute step 1 in the K_2 until the target element t is found from the ordered K_2; if $t < k_{\frac{U}{2}}$, then execute step 1 in the K_1 until the target element t is found from the ordered K_1.

In vector spatial data structure, it is well known that a simple curve is composed of a number of line segments. For a curve L, there are N coordinate vertices: $P = \{p_1, p_2, \ldots, p_i, \ldots, p_N\}, (i = 1, 2, \ldots, N)$, and the curve L is composed of some line segments, such as: $L = L'_{1,2} + L'_{2,3} + \ldots + L'_{i,j} + \ldots + L'_{N-1,N}$ (N is the number of the coordinate vertices). Figure 2, shows that curve L is composed of 26 coordinate vertices $(0, 1, 2, \ldots, 25)$. In the Gauss-Krueger plane rectangular coordinate system, the horizontal axis was the Y-axis, and the vertical axis was the X-axis. Along the Y-axis, L could be divided into two monotonic chains L'_i $(i = 0, 1, 2, \ldots, 13)$ and L'_{ji} $(j = 13, 14, \ldots, 25)$. For L'_i, along the Y-axis, vertex p_0 is the smallest, and the vertex p_{13} is the biggest, and L'_i is a monotonic increasing chain; For L'_j, along the Y-axis, vertex p_{13} is the biggest, and the vertex p_{25} is the smallest, and L'_j is a monotonic decreasing chain. When using the D–P algorithm to process the curve L, it should be noted that if the final result has self-intersection problems, it has been caused by the corresponding monotonic chains L'_i and L'_j.

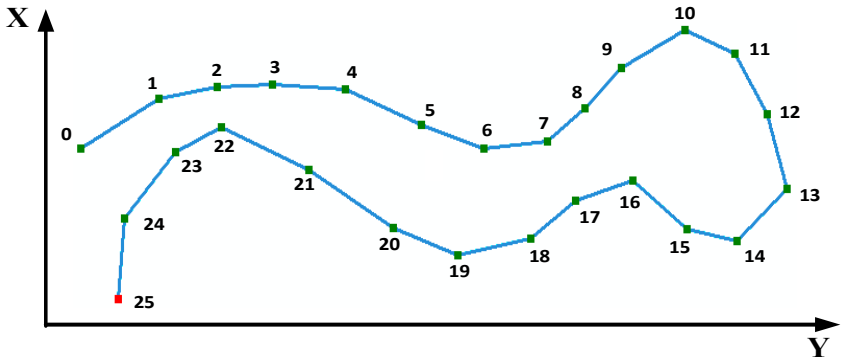


Figure 2. A schematic chart of the monotonic chain.

2.3. The New Vector Line Simplification Algorithm based on the D–P Algorithm, Monotonic Chains and Dichotomy

This paper used the monotonic chains and dichotomy to solve the self-intersection problem in spatial line simplification when processed by the D–P algorithm. In our proposed method, we firstly use the D–P algorithm to simplify the original polyline M, and obtain the simplified polyline T; Secondly, we check the self-intersection problems of T. If T does not have self-intersection problems, then we end this proposed method, otherwise, we use monotonic chain technology to quickly divide the T into several sequential monotonic chains; Thirdly, the dichotomy, MER (minimum-area enclosing rectangle, which refers to the rectangle with the smallest area that encloses the polyline) and geometric calculation method are used to process the sequential monotonic chains, in order to quickly locate the positions of the self-intersection problems of the sequential monotonic chains and solve the self-intersection problems, to obtain the final results.

This strategy of the proposed method does not only take the curve characteristics of a polyline into account, but also improves the time consumption of the proposed method. The main steps of the proposed method are described below.

Step 1: Use the D–P algorithm to process one curve M (There aren't self-intersection errors of M) and obtain a new curve T.

Step 2: Check the self-intersection problems of the T; if there are self-intersection errors, then perform step 3; otherwise, T is the final result of line simplification.

Step 3: For T, after step 2 of processing, if there are self-intersection errors, according to the sequence of the coordinate vertices, use the monotonic chain technology (as described in Section 2.2) to divide T into several sequential monotonic chains T_1', T_2', ... , T_i', ... , T_j', ... , T_n' $(i, j \in [1, n])$.

Step 4: For monotonic chains T_i' and T_j', which include and coordinate vertices, respectively, if $n \geq m$, then use the dichotomy to quickly divide T_i' into two monotonic chains: $L'_{1,t}$ and $L'_{t,n}$ $(t = \frac{n}{2}$, when n was even; or $t = \frac{n}{2} + 1$, when n was odd, n is an integer, and $n > 1)$, $L'_{1,t}$ and $L'_{t,n}$ are also two monotonic chains. Similarly, if $n < m$, then divide T_j' into two monotonic chains $S'_{1,t}$ and $S'_{t,m}$ $(t = \frac{m}{2}$, when m was even; or $t = \frac{m}{2} + 1$, when m was odd, m is an integer, and $m > 1)$, $S'_{1,t}$ and $S'_{t,m}$ are also two monotonic chains.

Step 5: If $n \geq m$, calculate the MER of $L'_{1,t}$, $L'_{t,n}$ and T'_j, respectively, as $R_{L_{1,t}}$, $R_{L_{t,n}}$ and R_{T_j}. Similarly, if $n < m$, calculate the MER of $S'_{1,t}$, $S'_{t,m}$ and T'_i, respectively, as $R_{S_{1,t}}$, $R_{S_{t,n}}$ and R_{T_i}.

Step 6: For $R_{L_{1,t}}$, $R_{L_{t,n}}$ and R_{T_j}, if $R_{L_{1,t}} \cap R_{T_j} = R_{L_{t,n}} \cap R_{T_j} = \phi$, then there is a non-intersection between T_i' and T_j'; If $R_{L_{1,t}} \cap R_{T_j} \neq \phi$, and $R_{L_{t,n}} \cap R_{T_j} = \phi$, then there may be an intersection problem between the monotonic chain $L'_{1,t}$ and T_j', and there is a non-intersection between $L'_{t,n}$ and T_j'; If $R_{L_{1,t}} \cap R_{T_j} = \phi$, and $R_{L_{t,n}} \cap R_{T_j} \neq \phi$, there may be an intersection problem between the monotonic chain $L'_{t,n}$ and T_j', and there is a non-intersection between $L'_{1,t}$ and T_j'; If $R_{L_{1,t}} \cap R_{T_j} \neq \phi$, and $R_{L_{t,n}} \cap R_{T_j} \neq \phi$, then there may be an intersection problem between the monotonic chain $L'_{1,t}$ and T_j', and there may be an intersection problem between the monotonic chain $L'_{t,n}$ and T_j'. Using the same method, we can calculate whether there are intersection problems between $R_{S_{1,t}}$, $R_{S_{t,n}}$, and R_{T_i}.

Step 7: Process all of the sequential monotonic chains $T_1', T_2', \ldots, T_i', \ldots, T_j', \ldots, T_n'$ $(i, j \in [1, n])$ using step 4, step 5, and step 6, until all the intersection problems of the monotonic chains are found.

Step 8: After processing by step 1 to step 7, all the intersection problems of the monotonic chains are found. In this step, we take an example to show how the proposed method deals with these intersection problems.

For one curve T, which is processed by the D–P algorithm as shown in Figure 3a, T includes 25 coordinate vertices. Using step 2 and step 3, we can obtain three monotonic chains T_1', T_2' and T_3' (as shown in Figure 3b); T_1' contains six coordinate vertices $(P_1, \ldots, P_6)$, and P_1 and P_6 are the end vertices of T_1'; T_2' contains nine coordinate vertices $(P_6, \ldots, P_{14})$, and P_6 and P_{14} are the end vertices of T_2'; T_3' contains 12 coordinate vertices $(P_{14}, \ldots, P_{25})$, and P_{14} and P_{25} are the end vertices of T_3'. After using step 4, step 5, step 6 and step 7, there is one intersection problem between T_1' and T_3', and there is another intersection problem between T_2' and T_3'.

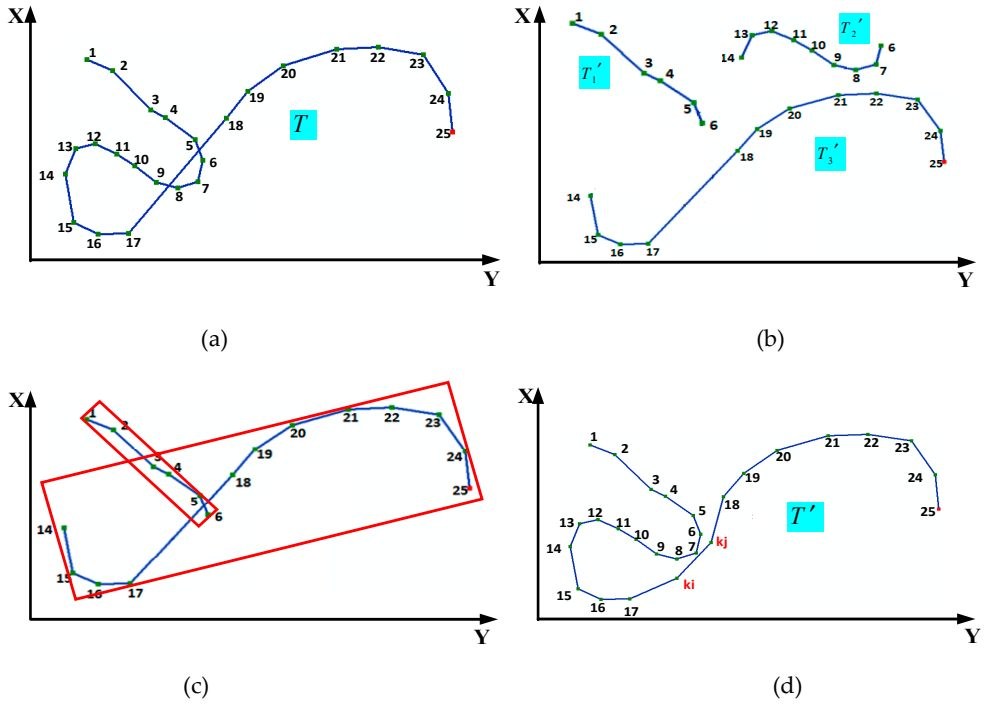


Figure 3. (**a**) The curve T which processed by D–P algorithm; (**b**) three monotonic chains T_1', T_2' and T_3' processed by the monotonic chain technology; (**c**) minimum-area enclosing rectangle (MER) of T_1' and T_3'; (**d**) the final result T'.

Using Figure 3c as an example, after processing by step 6, assuming that there is one intersection problem between T_1' and T_3', to obtain the intersection line segment $K_{5,6}$ and $K_{17,18}$ by the geometric calculation method [12,25] and obtain the coordinate vertices P_5, P_6, and P_{17}, P_{18}. If there are coordinate vertices $\left(v_p, v_{p+1}, \ldots v_i, \ldots, v_q, i \in [p, q]\right)$ (p, q are two integers) between P_{17} and P_{18} that belong to the original curve M, then calculate the shortest distance between the vertices $\left(v_p, v_{p+1}, \ldots v_i, \ldots, v_q, i \in [p, q]\right)$ and the line segment $K_{17,18}$ and find the maximum value ($D_{\max}$) of the shortest distance and the corresponding coordinated point P_i.

Connect $P_{17}P_i$, and P_iP_{18} and obtain two new monotonic chains T_{17i}' and T_{i18}'. Calculate whether there are intersection problems between the two new monotonic chains T_{17i}', T_{i18}' and the monotonic chain T_1'. If there are no intersection problems, then conclude this algorithm; the monotonic chain T_3' will be divided into two new monotonic chains T_{17i}' and T_{i18}'. If there are other intersection errors, then re-execute step 8 and step 9 until there is no intersection error between T_1' and T_3'.

Similarly, if there are coordinate vertices between P_5 and P_6 that belong to the original curve M, re-execute steps 8 and 9 until there is no intersection error between T_1' and T_3'.

Execute steps 4 to 8 until there are no intersection errors between all the monotonic chains, and then obtain the final result T'. Figure 3d shows the final result, k_i and k_j are two coordinate vertices from the original curve M.

Step 9: After processed by step 1 to step 8, all of the intersection problems have been processed, then end the proposed method, and obtain the final results.

3. Experiments and Analysis

We select two groups of experimental data to verify the validity of the proposed algorithm. The first group of data is the road line of Jiangxi Province in China. Its total length is approximately 1.56×10^5 km, and the data volume is approximately 92,000 bytes, including approximately 5.13×10^6 vertices. The second group of data is the land use line of Dingnan County in Jiangxi Province in China. Its total length is approximately 1.41×10^4 km, and the data volume is approximately 26,000 bytes, including approximately 1.24×10^6 vertices.

3.1. Assessment

In this study, we adopted a number of different methods to simplify the two groups of data and compare the performance of the proposed method. This is due to the ST algorithm [23], which is also based on the D–P algorithm, which could solve the self-intersection problems, in this paper, we compared the performance of the proposed method with the ST algorithm and the D–P algorithm.The scale of the experimental data is 1:10,000, and the results in target proportions of the original vertices are 60% and 70%, respectively. As a result, the two groups of the data are displayed as large volumes. Thus it is difficult to show case further details, in the same experimental environment. Moreover, we chose six self-intersection problems from the two groups of data instead. The simplified results of the six self-intersection problems are shown in Figure 4.

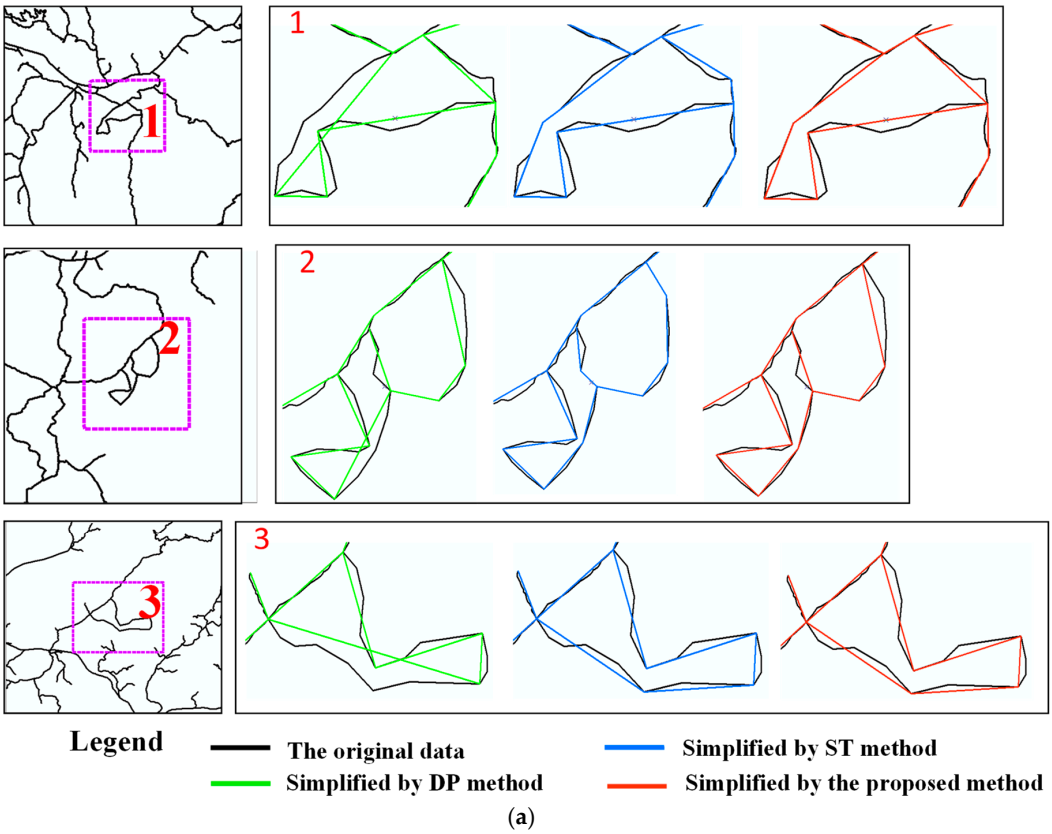


Figure 4. *Cont.*

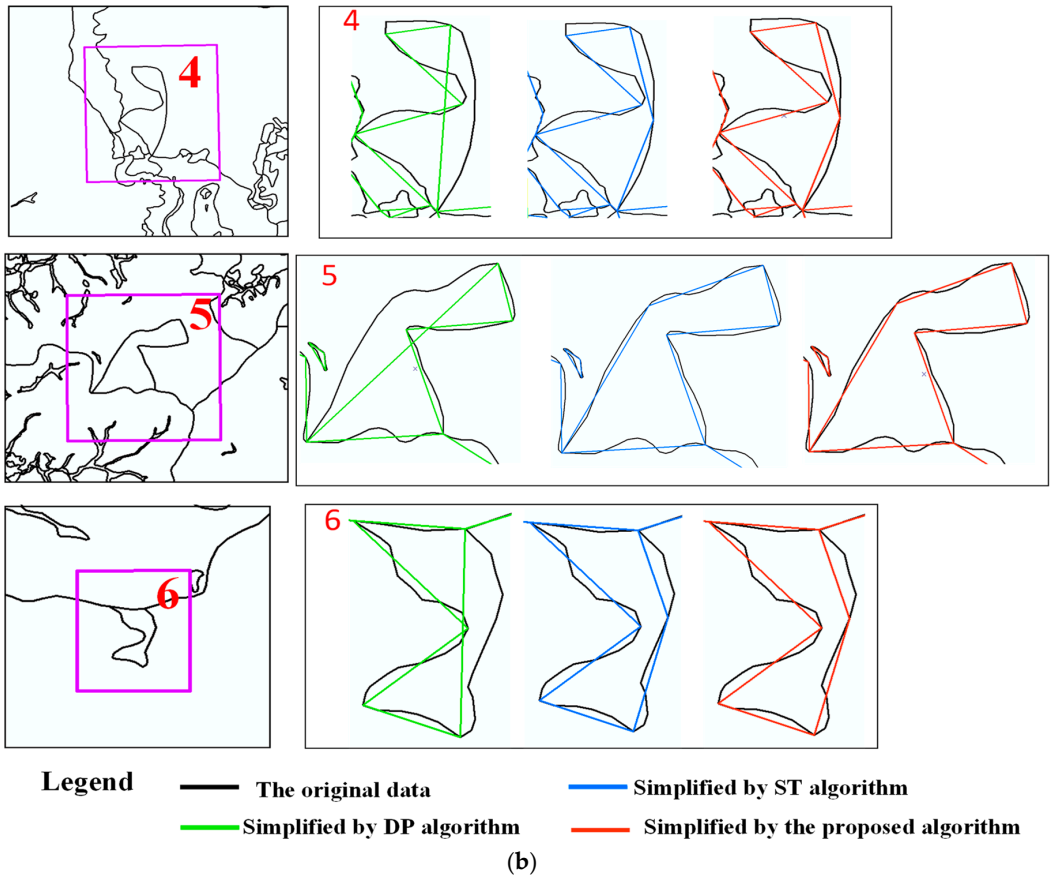


Figure 4. The six simplified results of the three applied methods from the two groups of data. (**a**) The three self-intersection problems identified from the first group of data; (**b**) the three self-intersection problems identified from the second group of data. Notes: DP algorithm is the Douglas–Peucker algorithm proposed by Douglas and Peucker [1]; ST algorithm is the star-shaped algorithm proposed by Wu and Marquez [23].

As is shown in Figure 4, the simplified results brought up from each group of data, the D–P algorithm produced self-intersection problems, but the proposed method could process self-intersection problems as well as the ST algorithm. To compare the performance of the different methods, four metrics are selected, including time consumption, mean vector displacement [3,26], Hausdorff distance (HD) [27], and standardized measure of displacement (SMD) [28].

Time consumption indicates how much time the algorithm takes.

Mean vector displacement is computed as the average displacement of the vector between the original vertices and the simplified version of the same vertices.

The Hausdorff distance (HD) between the two geometric objects is the largest minimum distance between points on one object to the other [27].

Standardized measure of displacement (SMD) is defined by Joao [28], and the calculation formula is demonstrated as follows:

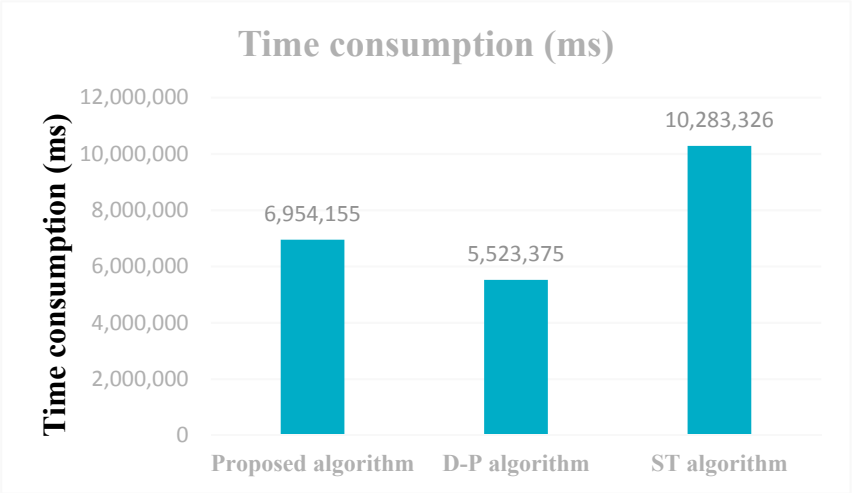
$$SMD(\%) = (1 - (W - O)/W) \times 100 \quad (1)$$

W is the distance from the coordinate vertices which has the maximum displacement between the original polyline and the simplified polyline to the straight line. This is obtained by connecting the first and last nodes of the polyline, and O is the actual displacement of the coordinate vertices between the original polyline and the simplified polyline.

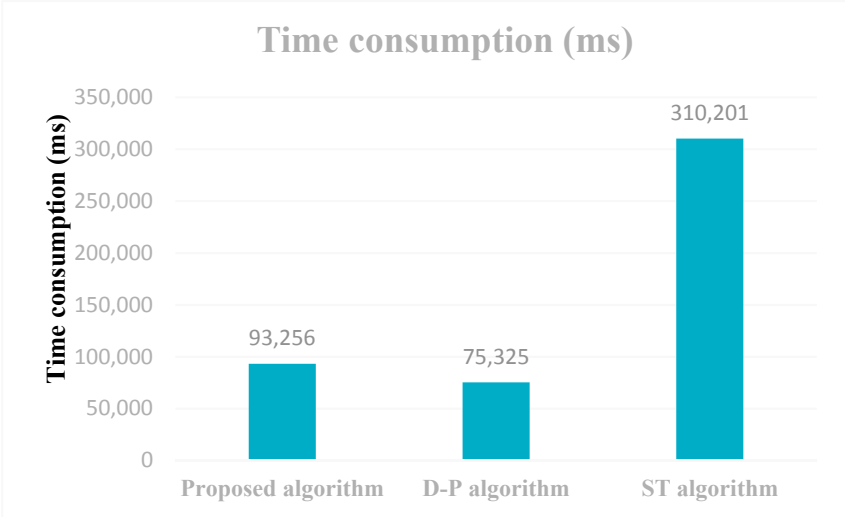
3.2. Results

The simplification assessment metrics of the data processed data by method are shown as follows: the resulting statistics are computed using the two groups of experimental datasets.

(1) Time consumption: the time consumption results of the three line simplification methods are shown in Figure 5, and the time consumption is measured in milliseconds (ms).



(**a**)



(**b**)

Figure 5. Time-consumption results. (**a**) Time consumption of the first group of data; (**b**) time consumption of the second group of data.

(2) Mean vector displacement: the mean vector displacement results of the three line simplification methods are shown in Figure 6. The mean vector displacement is measured in meters (m).

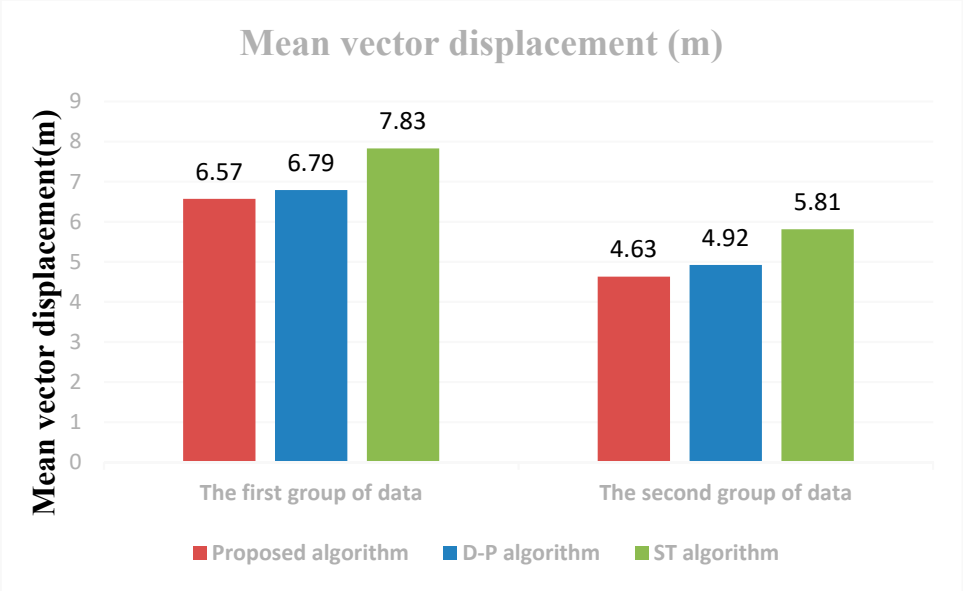


Figure 6. The mean vector displacement results (m).

(3) Hausdorff distance (HD): the Hausdorff distance (HD) results of the three line simplification methods are shown in Figure 7. The HD is measured in meters (m).

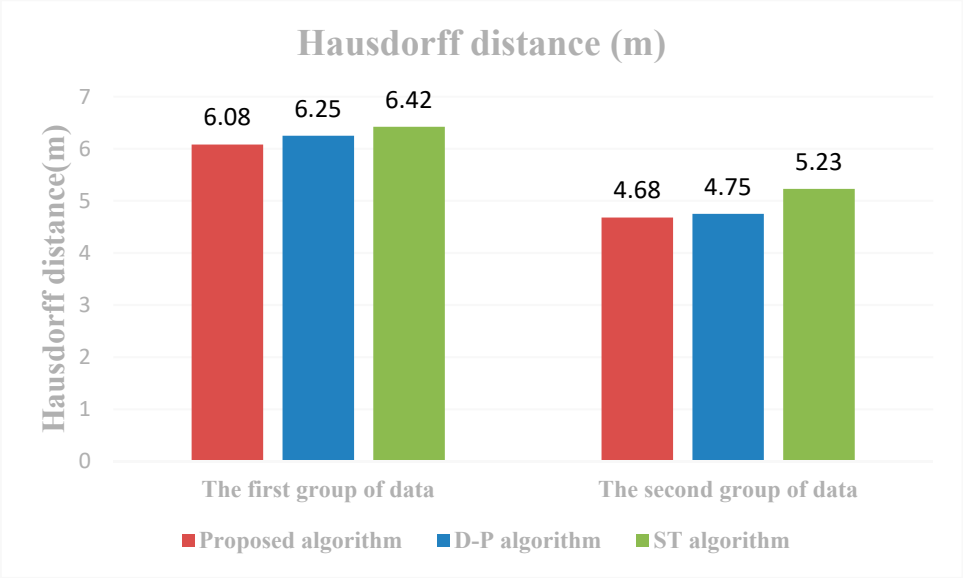


Figure 7. The Hausdorff distance results (m).

(4) Standardized measure of displacement (SMD): the standardized measure of displacement (SMD) results of the three line simplification methods are shown in Figure 8.

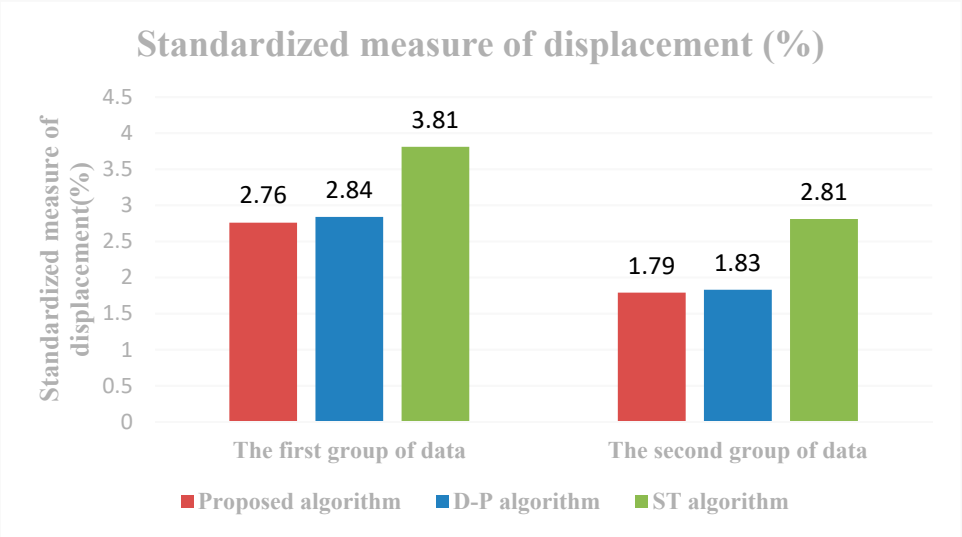


Figure 8. The standardized measure of displacement results (%).

3.3. Analysis

From Figure 5 to Figure 8, we observe the following:

(1) The proposed method can be used effectively for vector line simplification. We used two groups of data to verify the proposed method. It can be shown from the experimental results that the proposed method can not only solve the problem of self-intersection caused by the D–P algorithm but also has a high execution efficiency. Figure 4 shows the six results of simplifying the two groups of data using the three methods. In the six self-intersection problems as shown in the Figure 4, the polylines of six regions demonstrate complex curves with a number of hierarchical bends. As shown in Figure 4, the D–P algorithm produces self-intersection problems, but the proposed method and ST algorithm avoid these problems. This is due to the ST algorithm also being based on the D–P algorithm. As a result, the three methods identified the same experimental results in some cases.

(2) The D–P algorithm was found to have $O(nm)$ the worse case time and $O(n \log n)$ expected time, where n was the number of input vertices and m was the number of simplified polyline segments [23]; The ST algorithm was composed of mainly three steps; the worst case $O(nm)$ time complexity, where n was the number of input vertices and m depended on the number of star-shaped regions [23]. The proposed method in this paper involved two key steps: first, we first used the D–P algorithm to simplify the original curves and checked the self-intersection problems; then, we used the monotonic chain and dichotomy methods to address the self-intersection values. In the first step, our algorithm had the same execution time as the D–P algorithm. In the second step, our algorithm was carried out in $O(m \log m)$ time, while m was the number of self-intersection segments of simplified polylines.

The time consumption results of the three methods for processing the two groups of data are shown in Figure 5. For the first group of data, the time consumption results of the D–P algorithm, the proposed method and ST algorithm are 5,523,375 ms, 6,954,155 ms, and 10,283,326 ms, respectively. For the second group of data, the time consumption results of the D–P algorithm, the proposed method and ST algorithm are 75,325 ms, 93,256 ms, and 310,201 ms, respectively. It can be seen from the experimental results of each group of data that the time consumption of the proposed method is slightly higher than the D–P algorithm with the proposed method and, after the procession of the D–P algorithm, we use monotonic chains and dichotomy to modify the self-intersection problems. It is obvious that the time consumption of the proposed method is much lower than the ST algorithm. This is because the monotonic chains and dichotomy have high search efficiency and can quickly find and solve the self-intersection problems that are processed by the D–P algorithm.

(3) We use mean vector displacement to measure the location accuracy. As shown in Figure 6, the first group of data, the mean vector displacement results of the D–P algorithm, the proposed

method and ST algorithm are 6.79 m, 6.57 m, and 7.83 m, respectively, The second group of data showed that the mean vector displacement results of the D–P algorithm, the proposed method and ST algorithm are 4.92 m, 4.63 m, and 5.81 m, respectively. For each group of data, the mean vector displacement of the proposed method is similar to the D–P algorithm but much lower than the ST algorithm.

(4) Figure 7 shows the Hausdorff distance of the three methods for processing the two groups of data. For the first group of data, the Hausdorff distances of the D–P algorithm, the proposed method and ST algorithm are 6.25 m, 6.08 m, and 6.85, respectively. The second group of data showed, the Hausdorff distances of the D–P algorithm, the proposed method and ST algorithm are 4.75 m, 4.68 m, and 5.23 m, respectively. For each group of the data, the Hausdorff distance of the proposed method is similar to the D–P algorithm and the ST algorithm.

(5) We also used a standardized measure of displacement (SMD) to measure the location accuracy. As shown in Figure 8, the first group of data, the SMDs of the D–P algorithm, the proposed method, and ST algorithm are 3.46%, 3.58%, and 4.25%, respectively, The second group of data showed that the SMDs of the D–P algorithm, the proposed method and ST algorithm are 1.83%, 1.79%, and 2.81%, respectively. For each group of data, the mean vector displacement of the proposed method is similar to the D–P algorithm but much lower than the ST algorithm.

4. Conclusions

Vector line simplification is widely used in computer graphics, GIS, and others. The D–P algorithm is one of the most widely used methods for vector line simplification. When professionals use the D–P algorithm to address complex curves, we find it is easy to produce self-intersection problems. To further expand the application of the D–P algorithm, in this paper a new line simplification algorithm that combines the D–P algorithm, monotonic chains, and dichotomy is proposed. In the end, two experiments are designed to compare the results of our proposed method with the D–P algorithm and ST algorithm. From the result analysis, it is clear that the proposed algorithm has several advantages: (1) compared with the D–P algorithm, the proposed algorithm has the same execution efficiency but without self-intersection problems; (2) compared with the ST algorithm, the proposed method has the same ability to solve self-intersection problems but has better execution efficiency. At the same time, the proposed algorithm also has shortcomings to be further studied: (1) the proposed method focuses on the removal of self-intersection problems, however, the area preservation problems after the polyline simplification are not considered; (2) similar to the D–P algorithm, this proposed method does not consider the bending characteristics of the curves. In conclusion, these two thematic shortcomings will be the focus of our future research.

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