An Improved Algorithm with Azimuth Clustering for Detecting Turning Regions on GPS Trajectories

Kuo-Si Huang[1], and Yu-Chen Lin[2], Chang-Biau Yang[2†],
Ho-Chun Lin[3], Yung-Hsing Peng[4*] and Szu-Hsuan Wang[5]

[1] Department of Business Computing,
National Kaohsiung University of Science and Technology, Kaohsiung, Taiwan
[2] Department of Computer Science and Engineering,
National Sun Yat-sen University, Kaohsiung, Taiwan
[†] cbyang@cse.nsysu.edu.tw
[3] Chang Shen Tea Factory, Taoyuan, Taiwan
[4] Digital Transformation Research Institute,
Institute for Information Industry,Kaohsiung, Taiwan
[*] pengyh@iii.org.tw
[5] Myshine Technology Co., Ltd., Kaohsiung, Taiwan

Abstract. According to the latest report released by the Ministry of Agriculture (MOA) of Taiwan, the number of agriculture machinery in Taiwan exceeds 200,000. To keep track of these machinery, there are some research units making their efforts in devising GPS for agricultural application. Recently, Peng *et al*. proposed the turning region detection (TRD) problem for the GPS data obtained in the tea industry, which can be used to measure the working efficiency of agricultural machinery. To solve the TRD problem, Peng *et al*. tried to devise a linear time algorithm, which is easy to implement. However, the accuracy of their algorithm is far from expectation, which calls for further improvement. By adopting the concept of azimuth clustering, in this paper we propose a new algorithm for solving the TRD problem, which achieves better accuracy. The experimental results show that our new algorithm has an average accuracy 85%, which is better than the average accuracy 70% achieved with the previous algorithm. In addition, the proposed algorithm is not difficult to implement and is suitable for providing derivative services and analysis to agricultural managers in the future.

Keywords: GPS, Agri-machinery, Trajectory Analysis, Turning Region Detection.

1 Introduction

In Taiwan agriculture, agricultural machinery (agri-machinery) is extremely important to farmers because of the labor shortage [3,8,14]. Therefore, in recent years the Taiwan government adopts a strategic raise for agri-machinery subsidies. Back to 2019, the

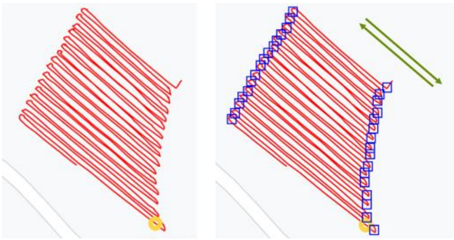
[† *] Corresponding Authors (Chang-Biau Yang and Yung-Hsing Peng)

total subsidies for Taiwanese farmers to purchase agri-machinery was first raised from NT$50 million to NT$1,600 million, which revealed the purpose of government to help farmers. Next, an annual investment of NT$2,300 million was issued from 2022 to 2025 to support the development of intelligent and energy-saving agri-machinery, aiming to increase the international competitiveness of Taiwan agriculture. To accomplish this goal, the collaboration between enterprises and research units is of high necessity.

Briefly, the research and development for agri-machinery can be categorized into two main types, which are the hardware construction [3,7] and the software establishment [5]. However, for the case in Taiwan, we notice that the development for agri-machinery software has not yet been widely discussed. In other words, the research for agri-machinery software remains worthy to be investigated. According to the statistics from the Ministry of Agriculture (MOA), there are more than 200,000 agri-machinery in Taiwan [8]. By using the global positioning system (GPS) [4,12,13], some researchers attempted to propose solutions for tracking the usage of agri-machinery, and most of them involve the techniques of data processing and computing algorithms [6.11]. Recently, by referring to the WAGRI platform [9], Peng *et al*. proposed the idea of agri-machinery data bank [10], which is designed to share machine data for developing agri-machinery services in the future. In their paper, Peng *et al*. collaborate with domestic companies to devise a GPS tracker suitable for agri-machinery, so that the trajectories of agri-machinery can be obtained and stored in the data bank.

In the practical application of trajectories, the turning region detection (TRD) problem needs to be solved. In the TRD problem, the input is a GPS trajectory containing n points, and the output is a bit string of length n–1, where 0 and 1 denote the straight tag and turning tag for a point, respectively. One can see that by solving the TRD problem, the working efficiency of agri-machinery can then be estimated by computing the straight speed and turning speed, which is helpful for agri-machinery management. In the previous result, Peng *et al*. devised a linear time algorithm that is easy to implement, and then utilized the algorithm to build cloud services for the agri-enterprise Chang Shen Tea Factory (CSTF). However, they mentioned that the accuracy of their algorithm requires improvement, according to their experimental results. In this paper, we propose an improved algorithm for the TRD algorithm, which is more feasible for developing cloud services for agri-machinery. Our new algorithm adopts the concept of azimuth clustering, so that the features of turning regions can be extracted more precisely. Experimental results show that our new algorithm outperforms the previous method, with the average accuracy improved from 70% to 85%.

The organization of this paper is as follows. In Section 2, we provide explanations for our method, including the formal definition of TRD problem and the detailed algorithm of our azimuth clustering approach. Section 3 presents the experimental results. Finally, we give conclusions and some future studies in Section 4.



(a) (b)

Fig. 1. A visual example of the sample trajectory with 3122 points in the database uploaded by the GPS tracker [10]. (a) The visualization for the machine trajectory in the red points. (b) Turning regions indicated by the blue squares.

2 Methodology

2.1 GPS Trajectory and Turning Region Detection

For agricultural management, automatic collection of agricultural activities is very important when it comes to the labor shortage issue. Therefore, in previous research Peng *et al*. [10] devised a GPS tracker that can record and report the movement of agricultural machine. This GPS tracker adopts the u-blox NEO-M8 series module, and the tracker is available to be used in our paper. For ease of understanding, here we begin the explanations for variables. First, the GPS tracker collects the data in the form of (ID, t, lat, lon) and automatically upload the data to the server. For a record (ID, t, lat, lon), ID represents the unique identification of the GPS tracker, t refers to the recorded time of this record, lat and lon are the latitude and longitude of that corresponding location, respectively. Given a GPS trajectory containing n points, the turning region detection (TRD) problem [10] tries to output a bit-sequence of length n, where 0 and 1 denote the straight tag and turning tag for a point, respectively. Fig. 1 shows a visual example of the sample trajectory with 3122 points in the database uploaded by the GPS tracker. In Fig. 1, the red points and blue squares (Fig. 1(b)) refer to the trajectory and turning regions of this machine.

Once the trajectories of working machinery are collected, we can evaluate the experience and analyze the efficiency by examining the driving behavior for straight regions and turning regions. In turning regions, newcomers would be less effective than experienced drivers. In the TRD problem, $P = \{p_1, p_2, \ldots, p_n\}$ denotes a trajectory of n ordered GPS points, where $p_i = (lat_i, lon_i)$, the ith point in P, composed of its latitude lat_i and longitude lon_i. Given a trajectory P, the TRD problem tries to obtain a binary sequence to indicates that if p_i is in a turning region or not. In fact, if we plot the points in trajectory P on a map, one can easily identify turning regions based on this visualization. In Fig. 1(b), the blue squares are artificially marked with human examination. However, it is obviously a waste of time for human to process a large number of trajectories. Therefore, the TRD algorithm is very useful for developing automatic processing approach with computer analysis.

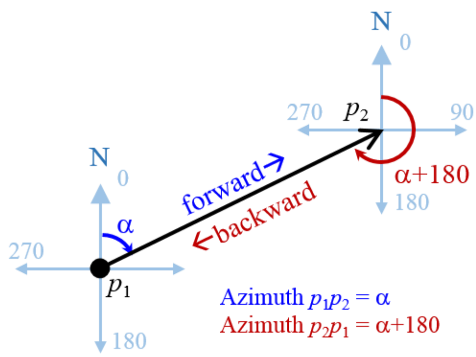


Fig. 2. An example of the forward and backward azimuths of p_1p_2, where p_1 and p_2 are the source and the destination, respectively.

2.2 Azimuth and Navigation

Azimuth or whole circle bearing (WCB) [2] is widely used in conjunction with the prismatic compass or the modern GPS for navigation. The azimuth, usually denoted α, is a horizontal angle measured clockwise from a north base line or meridian. It varies from 0 to 360 degrees in the clockwise direction relative to the north, where north, east, south, and west directions refer to 0, 90, 180, and 270 degrees, respectively. In addition, p_1p_2 means from point p_1 to point p_2, that is, p_1 and p_2 are source and destination. Fig. 2 shows the forward and backward azimuths corresponding to the azimuths of p_1p_2 and p_2p_1, respectively.

In cartography, the forward azimuth of p_1p_2 in decimal degrees can be calculated by the cartographic coordinates of two points $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ in a flat plane as Equation 1.

$$\alpha(p_1, p_2) = \frac{180}{\pi}\operatorname{atan2}(x_2 - x_1, y_2 - y_1) \tag{2}$$

2.3 Working Direction and Displacement

On the farmland, the tea trees are planted in rows with working pathways between them. These pathways give spaces for farmers and equipment to move and operate. It can be observed that there are parallel straight lines in Fig. 1, and they follow some specific directions. We refer to these specific directions as the working azimuth z^*. Additionally, the forward and backward azimuths share specific departure and return pathways and we can operate along both directions. Taking Fig. 1 as an example, in the trajectory, one can observe that many segments share the two azimuths of the two green arrows in Fig. 1(b). Heavy agricultural machinery must move on the farm pathways according to the working direction z^* or the complementary direction of z^*, otherwise it will destroy some tea trees.

The movement speed of the machine is another important indicator of its working state. A steady movement speed can indicate that it is in a normal operating state. If the movement speed is unstable, it indicates that the machine may encounter abnormal events in the tea garden, such as obstacles in the pathway, malfunctions of machine, or out of fuels. Additionally, drivers often slow down when making turns, which is a common behavior. The working speed corresponds to the displacement under a certain time between two points p_i and p_{i+1}. Equations 3 and 4 give the haversine formula hav(p_1, p_2) and its corresponding formula $\Delta(p_1, p_2)$ for calculating the displacement between $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ via their latitudes and longitudes, where 6371000 is the mean radius of the earth in meters (6371km) [2].

$$\mathrm{hav}(p_1, p_2) = \sin^2\left(\frac{x_2 - x_1}{2}\right) + \cos(x_1) \times \cos(x_2) \times \sin^2\left(\frac{y_2 - y_1}{2}\right) \tag{5}$$

$$\Delta(p_1, p_2) = 6371000 \times 2 \times \mathrm{atan2}\left(\sqrt{\mathrm{hav}(p_1, p_2)}, \sqrt{1 - \mathrm{hav}(p_1, p_2)}\right) \tag{6}$$

2.4 Our Algorithms

Based on the above preliminaries, the main steps of our TRD algorithm are described as follows, which is a variant and improved version of the TRD algorithm [10] proposed by Peng *et al*. Based on the output binary sequence B, it can be used to identify each point p_i in the turning or working area. We can also compress B by run-length encoding to count revolutions.

Algorithm 1 TRD: Turning Regions Detection.

Input: A trajectory $P=\{p_1, p_2, \ldots, p_n\}$ of n ordered GPS points, where $p_i=(lat_i, lon_i)$.
Output: A binary sequence $B=\{b_1, b_2, \ldots, b_{n-1}\}$, $b_i=1$ if p_i is in a turning region.

1. Calculate the direction sequence $Z = \{z_1, z_2, \ldots, z_{n-1}\}$ with $z_i = \alpha(p_i, p_{i+1})$, where z_i denotes the local moving direction from p_i to p_{i+1}.
2. Calculate the displacement sequence $R = \{r_1, r_2, \ldots, r_{n-1}\}$ with $r_i = \Delta(p_i, p_{i+1})$, where r_i denotes the local displacement from p_i to p_{i+1}.
3. Determine the pivotal working direction z^* by segment clustering in meaningful Z and R.
4. Set a threshold θ. Report $b_i = 0$ if z_i is close to z^* within θ. Otherwise, report $b_i = 1$.
5. **Return** B.

In Algorithm 1, Steps 1 and 2 calculate the local moving direction z_i and displacement r_i from p_i to p_{i+1}, which take linear time. In order to obtain the working direction z^*, many algorithmic strategies in machine learning (ML), deep learning (DL) and artificial intelligence (AI) can be applied, such as linear discriminant analysis (LDA), k-means clustering, and decision tree [1]. Many ML and AI algorithms and strategies can be used to solve difficult problems, but they can be computationally expensive. Since Steps 1 and 2 can be done in linear time, and the input P of the TRD problem is a sequence, we tend to use linear time or sub-quadratic time algorithms to find the z^*.

In the input trajectory P, each $p_i = (lat_i, lon_i)$ is a pair of floating points. Note that in Z, each z_i is a value of an azimuth limited to a range between 0 and 360, which can be transformed from trajectory P. One can see that it is much easier to deal with the sequence Z of one-dimensional elements than the sequence P of two-dimensional elements. In addition, we develop Algorithm 2 to detect the pivotal working direction z^*, where z^* is the most frequently occurring direction in Z.

Algorithm 2 zStar: Pivotal Direction Detection.

Input: A sequence $Z = \{z_1, z_2, \ldots, z_{n-1}\}$ of azimuth values.
Output: The pivotal working direction z^*.

1. Convert each $z_i \in Z$ to its nearest integer, obtaining the integer sequence $U = \{u_1, u_2, \ldots, u_{n-1}\}$, where u_i denotes the corresponding integer of z_i.
2. Set q buckets, then count the occurrence of azimuths in U by using the buckets, and z^* or its complementary will be in the bucket with most occurrences.
3. Check the most frequently occurring azimuth buckets to make z^* meaningful.
4. **Return** z^*.

In fact, one can easily apply the modulo operation to put integers $u_i \in U$ into corresponding buckets by a single linear scan, or apply the concept of counting sort. Therefore, Algorithm 2 can be completed in O(n) time, satisfying the linear time requirement of Algorithm 1. Due to the characteristics of farmland, such as the shape or topography of tea gardens, especially that in mountainous areas, there may be several pivotal working directions. This means that for a trajectory P, there may be multiple working directions of pathways existing in a tea garden. In Algorithm 2, the variables can be modified to suit the requirements of different situations.

3 Experiments

The experimental dataset is provided by the Chang Shen Tea Factory (CSTF), a well-known agri-enterprise in tea industry. The CSTF has won many agricultural awards from the Ministry of Agriculture, and also has a strong interest in developing smart agricultural services. With the approval of CSTF, we can analyze individual trajectories collected from machines and tea gardens. The experimental criteria and results are presented as follows.

3.1 Experimental Results

Based on the definition of the TRD problem, the pivotal working direction z^* and the binary sequence B are two main outputs in this paper. They can be used to indicate the turning and straight regions in trajectory P. In our experiments, we compare the number of turns for each case with the number of turns labeled by humans. This comparison can be used to evaluate the performance of related algorithms and understand gaps in practical applications.

The TRD algorithm proposed by Peng *et al.* [10] requires a threshold θ to obtain the binary sequence B. The threshold θ affects the result of the number of turns. There is another threshold l to determine whether a possible turn can be ignored when the turning time (run length) is less than a certain limitation. According to the actual observation in the tea garden, it usually takes more than 10 seconds to make a normal turn. In this paper, we take the threshold $(l,\theta) = (10,5)$ to implement Peng's algorithm, which represents the best results in the previous paper [10].

In our experiments, there are 12 cases provided by the CSTF, and the first six cases are the same with those used in Peng's paper. Table 1 shows the comparison of Peng's TRD algorithm [10] and the proposed algorithm. The value in Table 2 indicates the number of turns for each test case. The value in column $\#S_H$ indicates the number of turns confirmed by manual inspection. In other words, the values in column $\#S_H$ are the targets of the proposed algorithms. Experimental results show that the proposed algorithm outperforms the previous TRD algorithm. More precisely, the proposed algorithm has an average accuracy 85%, better than the average accuracy 70% achieved with previous algorithm.

Table 3. Comparison of experimental results with 12 cases, where TRD(5,10) represents the TRD algorithm [10] with $(l,\theta) = (5,10)$.

Cases	Length n=|P|	$\#S_H$ (obj.)	TRD(5,10) [10]	Our Algorithm
(1)	3122	32	26	32
(2)	4061	26	22	24
(3)	6039	37	63	30
(4)	7241	80	100	86
(5)	5309	46	33	53
(6)	4192	19	50	30
(7)	3868	64	58	61
(8)	2651	40	45	45
(9)	3427	10	33	11
(10)	3762	45	56	41
(11)	2201	8	28	9
(12)	5156	21	46	23

3.2 Visualization from Trajectory to Azimuth

In order to present the azimuth effect in the visualization, we take Fig. 3 to show the azimuth sequence Z of Case (1), where Case (1) has 3122 points with azimuth values between 0 to 360. It is not difficult to see that in the turning area, the azimuth values change greatly; while in the working pathway, the azimuth values are similar. By observing Fig. 3, we can easily conclude that there are 32 turns in Case (1).

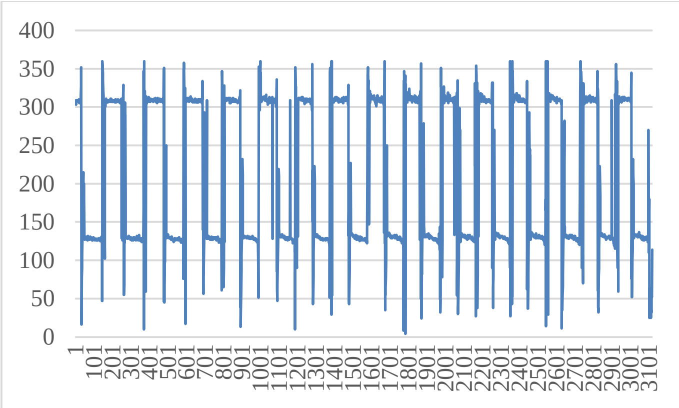


Fig. 3. A visualization for azimuth sequence Z of Case (1), where n = 3122.

3.3 Visualization from Trajectory to Azimuth with Displacement

Fig. 4 shows the azimuth sequence Z of Case (2), where Case (2) has 4061 points and each $z_i \in Z$ is between 0 to 360. In the first 200 points, it is difficult to determine if each point in the area is in the turning region or not. By calculating and observing the displacement sequence R associated with the local speed, we find that small displacement and low moving speeds occur in the first 200 points. The machine may be stationary while its engine is running, so the GPS may report a different position due to vibration.

Fig. 5 shows the azimuth sequence Z and displacement sequence R for each point, where it is possible that the first 200 points might be in stationary status when the engine is running. Based on the observation, we try to use the displacement sequence R as an additional condition to detect turning regions. In the preliminary experiments, if $r_i <$ 0.2 (m/s), we consider it is not in the working state. We design a filtering rule by combining displacement R with threshold δ, $(((r_i < \delta)?0{:}1)+((r_i = 0)?1{:}0))$, and apply this rule as shown in Fig. 6. Therefore, in Fig. 6, the orange points hide some azimuth points. It can be seen that there are 23 working segments in the exposed area, so we conclude that there are 24 turns in Case (2).

Fig. 7 and 8 show the comparison of 12 cases for thresholds δ = 0.2 and δ = 0.05. In the visual comparison, it can be seen that the smaller threshold δ = 0.05 can be used to hide more noise points, so that the points in the pathways can be easily identified.

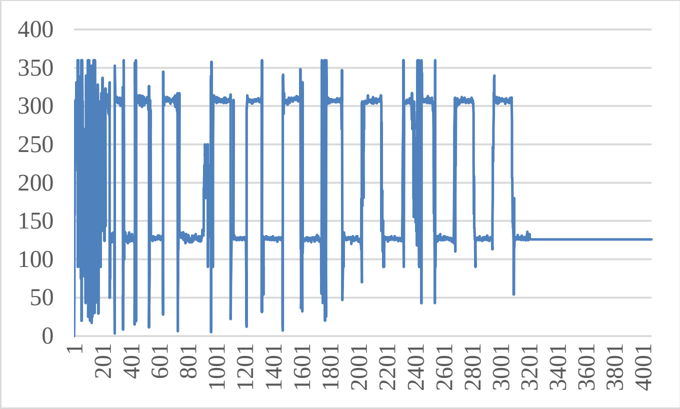


Fig. 4. A visualization of azimuth sequence Z of Case (2), where n = 4061.

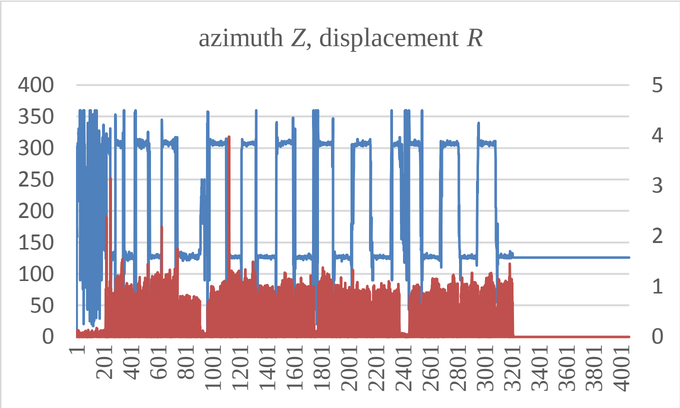


Fig. 5. A visualization of azimuth Z and displacement sequence R (meters, in red) of Case (2).

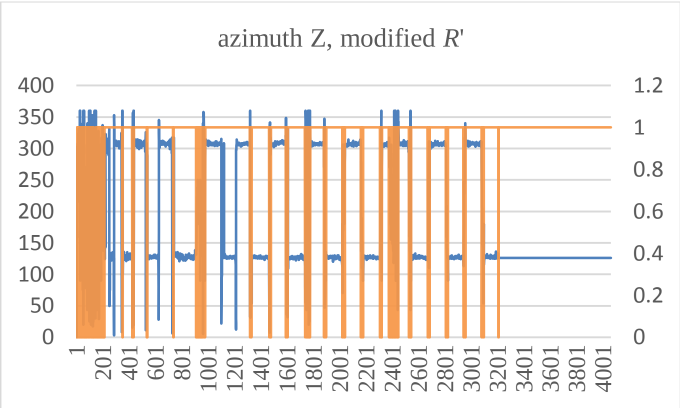


Fig. 6. A visualization of azimuth Z and modified rule R' (δ = 0.2, in orange) of Case (2).

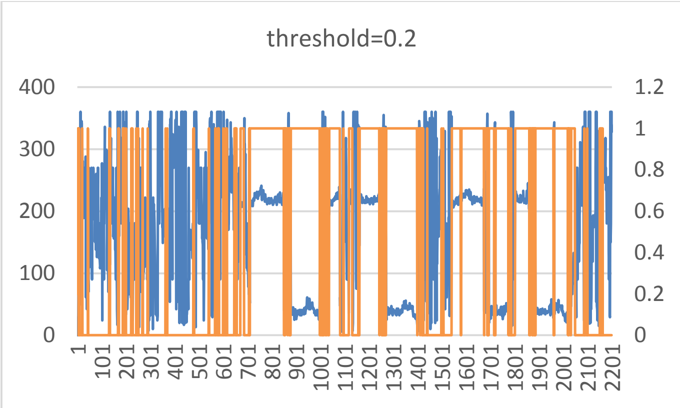


Fig. 7. A visualization of azimuth Z and modified rule R' (δ = 0.2, in orange) of Case (11), where n = 2201.

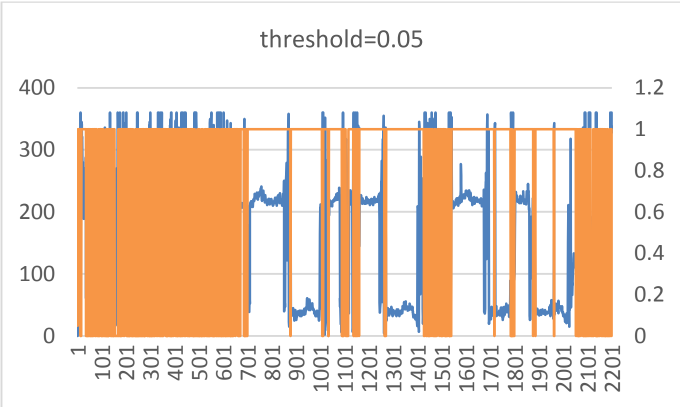


Fig. 8. A visualization of azimuth Z and modified rule R' (δ = 0.05, in orange) of Case (11), where n = 2201.

4 Conclusions

There are many study on GPS application. Recently, Peng *et al*. (2023) proposed the turning region detection (TRD) problem for the GPS trajectories obtained in the tea industry, which can be used to measure the working efficiency of agricultural machinery. To solve the TRD problem, Peng *et al*. tried to devise a linear time algorithm, which is easy to implement. In this paper, we take consideration of the azimuth and displacement from the original trajectory, and show that they can be used to improve the original result. By combining the azimuth and displacement of each point in the trajectory, we propose a new algorithm for the TRD problem. The experimental results show that the proposed algorithm has an average accuracy 85%, which is better than the average accuracy 70% achieved with previous algorithm. In addition, the proposed algorithm is also not difficult to implement, which is suitable for providing derivative services and analysis to agricultural managers.

There are some possible ways for future study. One may try to optimize the threshold δ with more test cases to improve the accuracy by other machine learning (ML) algorithms or strategies. In addition, we can try to design algorithms with higher complexity to obtain better results, such as the convex hull finding and pattern matching. Finally, according to the fact that our experiment involves the number of turns inspected by human, it is worthwhile to investigate and involve deep learning (DL) algorithms and artificial intelligence (AI) for future improvement.

References

1. Alpaydın, E.: Introduction to Machine Learning. The MIT Press, 4th edn. (2020).
2. DiBiase, D.: Nature of Geographic Information: An Open Geospatial Textbook. Pennsylvania State University, College of Earth and Mineral Sciences (2014).
3. Huang, W.Y., Liu, T.L.: The development of a new cutting machine for tea harvester. In: The Professional Report of Tea Industry in Taiwan. vol. 122, pp. 13–14 (Dec 2022). https://www.tbrs.gov.tw/ws.php?id=4131
4. Jiang, L., Chen, C.X., Chen, C.: L2MM: Learning to map matching with deep models for low-quality GPS trajectory data. ACM Transactions on Knowledge Discovery from Data 17(3), 1–25 (Feb 2023).
5. Kurdi, M.M., Elzein, I.A.: Trajectory and motion for agricultural robot. In: 2022 International Conference on Decision Aid Sciences and Applications (DASA), pp. 1430–1434. Thailand (Mar 2022).
6. Lo, S.F., Tseng, K.T., Yang, C.B., Huang, K.S.: A diagonal-based algorithm for the longest common increasing subsequence problem. Theoretical Computer Science 815, 69–78 (2020).
7. Manikandan, S., Kaliyaperumal, G., Hakak, S., Gadekallu, T.R.: Curve-aware model predictive control (C-MPC) trajectory tracking for automated guided vehicle (AGV) over on-road, in-door, and agricultural-land. Sustainability 14(19), 12021 (2022).
8. Ministry of Agriculture, Taiwan: Taiwan Agricultural Statistics Website. https://agrstat.moa.gov.tw/sdweb/public/inquiry/InquireAdvance.aspx
9. National Agriculture and Food Research Organization (NARO), Japan: The WAGRI Platform in Japan, https://wagri.naro.go.jp/
10. Peng, Y.H., Chen, Y.H., Lin, H.C., Huang, P.C., Lee, C.P.: The development of agricultural machinery data bank with GPS as an application study. In: Proceedings of the 40th Workshop on Combinatorial Mathematics and Computation Theory (CMCT2023). Taoyuan, Taiwan (May 19-20 2023).
11. Peng, Y.H., Yang, C.B.: Finding the gapped longest common subsequence by incremental suffix maximum queries. Information and Computation 237, 95–100 (2014).
12. Wang, C.Z., Kong, L.W., Jiang, J., Lai, Y.C.: Machine learning-based approach to GPS antijamming. GPS Solutions 25(3), 115 (2021).
13. Wei, X., Wang, Y., Sun, C.: PerDet: Machine-learning-based UAV GPS spoofing detection using perception data. Remote Sensing 14(19), 4925 (2022).
14. Wu, H.C.: Discussion on the structure of current agricultural human resources. In: The seasonal report of technical service in Taiwan Agriculture Research Institute (TARI). vol. 118,

pp. 36–39 (June 2019). https://scholars.tari.gov.tw/bitstream/123456789/11963/1/30-2-8.pdf