Temporal Analysis of Partial Moving Patterns Identified from Large Trajectory Datasets: a Case Study of Ocean Eddies in the South China Sea

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Abstract—**Trajectory data not only contains spatial locations but also rich temporal information. Discovering the temporal characteristics of trajectories is essential for understanding the dynamics of partial moving patterns. This paper presents an analysis approach to exploring temporal features of moving objects. The method first extracted representative routes from original trajectories, and then calculated the dominant time span of each line segment of the traveling routes, and finally visualized the routes on the map for subsequent analysis. Ocean eddies which are frequently observed in the South China Sea (SCS) were selected as a case study to test the utility of this approach. The time heterogeneity of the identified moving paths revealed potential seasonal movements of eddies, which demonstrated the ability of this analysis method to discover dynamic patterns from trajectories.**

Keywords- temporal analysis; moving patterns; trajectory data mining; ocean eddies

I. INTRODUCTION

In the contemporary big data era, fast development of technologies such satellite observation, GPS, and smart mobile devices enables us to collect large volumes of track data about geography, environment, and humans. How to discover valuable knowledge from the complicated, big moving data is becoming a pressing challenge.

Trajectory datasets record not only location information but also timestamps of moving objects. They can be visualized as lines on a two-dimensional space or space-time paths on a three-dimensional space [1]. Many trajectory data mining studies have been carried out to discover common patterns of moving objects. A group of the studies have focused on finding the patterns of the whole trajectory [2-4], which are generally clustered by measuring the similarity between the whole trajectories [5, 6]. However, valuable moving patterns may also be concealed in some parts of the long trajectories. Therefore, a partition-and-group framework for discovering partial moving patterns was proposed by Lee J. G. et al. [7], which employed the DBSCAN algorithm to cluster line segments of trajectories, and delineates each group by a representative path.

Although the partition-and-group framework is able to identify partial moving patterns from large trajectory datasets, it lacks the ability to reveal underlying temporal characteristics of the discovered common paths. Therefore, this study presents an analysis approach to reveal the temporal dynamics of moving patterns. It first clusters the trajectories by the partition-and-group framework, then calculates the temporal features of each partial moving pattern, and finally displays the temporal and spatial characteristics on a map.

The rest of this paper is organized as follows. Section 2 describes the temporal analysis method developed on partial moving patterns. Section 3 presents a case study of ocean eddies to validate the utility of the method. Finally, Section 4 concludes the paper.

II. METHODS

In order to discover spatial and temporal characteristics of moving objects, we first extracted spatial features by identifying partial moving patterns, and then analyzed and visualized their temporal attribute.

A. Identify partial moving patterns

According to the partition-and-group framework [7], there are mainly three steps involved in identifying partial moving patterns.

Firstly, trajectories are partitioned into line segments at characteristic points. These points are selected from nodes of original trajectories satisfying the minimum description length (MDL) principle [7]. It is a procedure of simplifying original trajectories and the MDL principle finds the optimal tradeoff between preciseness and conciseness.

Line segments are then grouped into clusters using the algorithm DBSCAN [7]. DBSCAN is extended here for line clustering. The distance measurement between line segments is adapted and consists of three components: the perpendicular distance, the parallel distance, and the angle distance. Whether two different line segments belong to the same cluster is determined by whether they are density-connected. Since different line segments may be extracted from the same trajectory, to explain the common behavior of different trajectories, the number of trajectories also needs to be restricted.

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Finally, representative trajectories are generalized from line segments belonging to the same cluster. The representative trajectory is an imaginary trajectory that indicates the major behavior of partial trajectories. It is a sequence of points which are determined by a sweep line approach. When sweeping a vertical line across line segments, if the number of line segments hitting sweeping line is greater than the given minimum, the average coordinate of these intersection points is calculated and added into the representative trajectory.

B. Temporal Analysis and Visualization

The identified representative trajectories only revealed spatial characteristics. From these routes, we easily recognized where moving objects frequently pass or long-term exist, but we were not able to make sure when these happened. In order to compensate for this deficiency, we made a temporal analysis which calculated the dominant time span of every segment of representative trajectories, and then visualized their temporal attribute on a map. For every segment of representative trajectories, we calculated the projection time span of line segments simplified from the original trajectories, counted the number of periods sharing the same time span, and took the largest one as the dominant period. The calculation of projection time span is shown by Fig. 1.

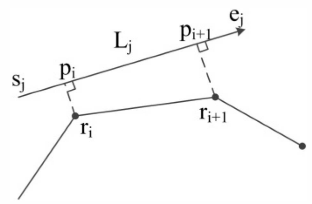

Figure 1. An example of a representative trajectory and one of its participated line segments. Points r_i and r_{i+1} are on the representative trajectory. L_j represents one of line segments simplified from original trajectories. Point p_i and p_{i+1} are projection points of r_i and r_{i+1} onto L_j.

We supposed that in one line segment, time linearly increased from the starting point to the ending point. Since the time of s_j and e_j were recorded, we could calculate the time of p_i and p_{i+1} by linear interpolation, and then the period from p_i to p_{i+1} was the projection time span of r_i and r_{i+1} on L_j.

Based on the statistical result, we drew the dominant time span of every segment on a map with different widths describing the number of line segments sharing the same period and different colors describing the attribute of this period, for example in day or night, and in summer or winter. The color of the line reflected temporal characteristics while the width reflected the reliability of them.

III. CASE STUDY

We used real trajectory datasets of ocean eddies to verify the utility of our temporal analysis method.

A. Movement of ocean eddies

Ocean eddies play an important role in transporting energy and matter across the ocean and have been a research focus in oceanography for years [8-10]. In our previous study, we have automatically detected and tracked the evolution processes of ocean eddy in the South China Sea (SCS) during 1992-2012 [11, 12]. Each eddy process is stored as a sequential connection of points with coordinates and time. Trajectories of 816 strong eddies with long travelling distance are selected for discovering the partial moving patterns and analyzing the temporal characteristics of ocean eddies. According to the rotation manner, ocean eddies are divided into anticyclonic and cyclonic eddies; anticyclonic eddies rotate clockwise in the northern hemisphere while cyclonic eddies rotate anticlockwise. Given the different generation dynamics, the two types of eddy were discussed apart in our analysis.

B. Partial Moving Patterns

According to the procedure of identifying partial moving patterns introduced in Part Ⅱ A, trajectories of 398 anticyclonic and 418 cyclonic eddies were experimented respectively to discover eddies' representative routes. The distribution of representative trajectories extracted by our experiment is presented in Fig. 2.

Partial moving patterns of eddies in the SCS distributed in three regions: the north continent slope, the central basin, and offshore of central Vietnam (Fig. 2). With the influence of submarine topography, eddies in the SCS frequently move along the north continent slope [13, 14]. In the northern SCS, the identified representative trajectory of anticyclonic eddy originated west of the Luzon Strait, propagated westward along the north continent slope, and disappeared near the western boundary (Fig. 2a). The representative trajectory of cyclonic eddies displayed similar patterns, only the location of origin lied eastward (Fig. 2b). The moving pattern along the north continent slope was the most significant one in our experiment result, which was consistent with previous research.

Affected by the Southeast Asian monsoon system and the large scale current, eddies in the SCS present annual and seasonal variations [15, 16]. Therefore, besides extracting paths of frequently passing eddies, we also expect to find out when these patterns exist. A further study on temporal characteristics extraction and analysis is necessary.

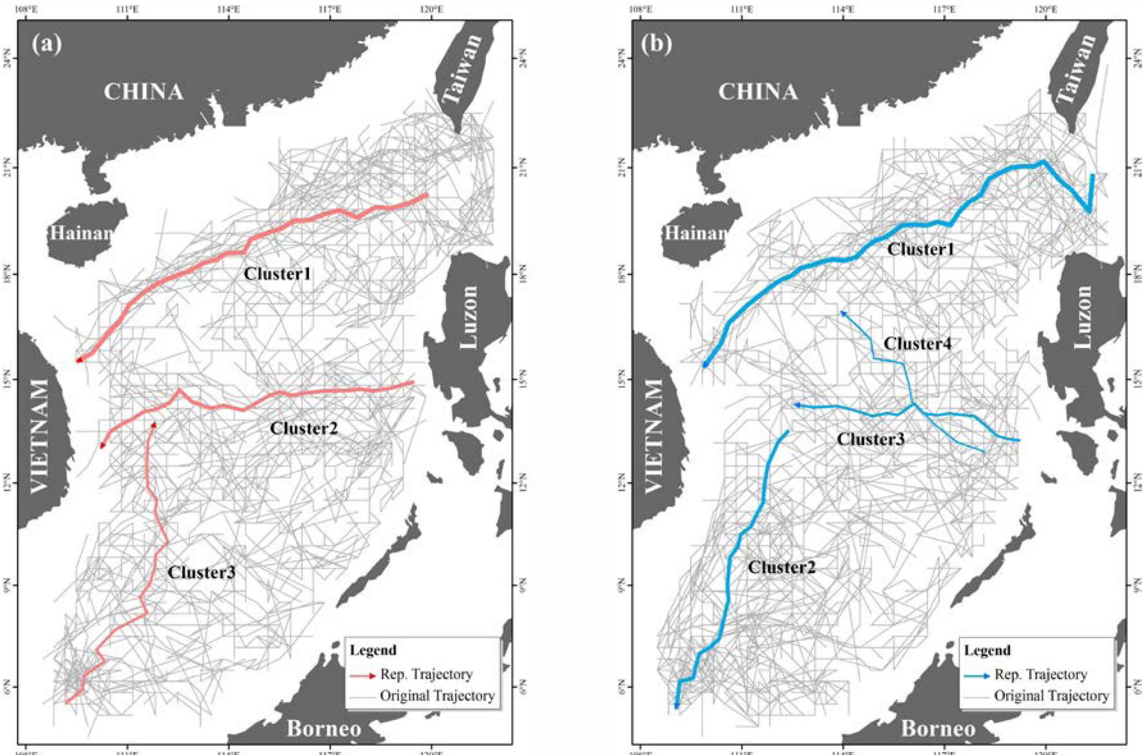

Figure 2. Partial moving patterns of ocean eddies in the SCS: (a)anticyclonic eddies; (b)cyclonic eddies. Representative trajectories (red/blue lines) are identified from original trajectories (gray lines). The width of line indicates the number of trajectories participating in this cluster; the more trajectories participating in, the wider the line is.

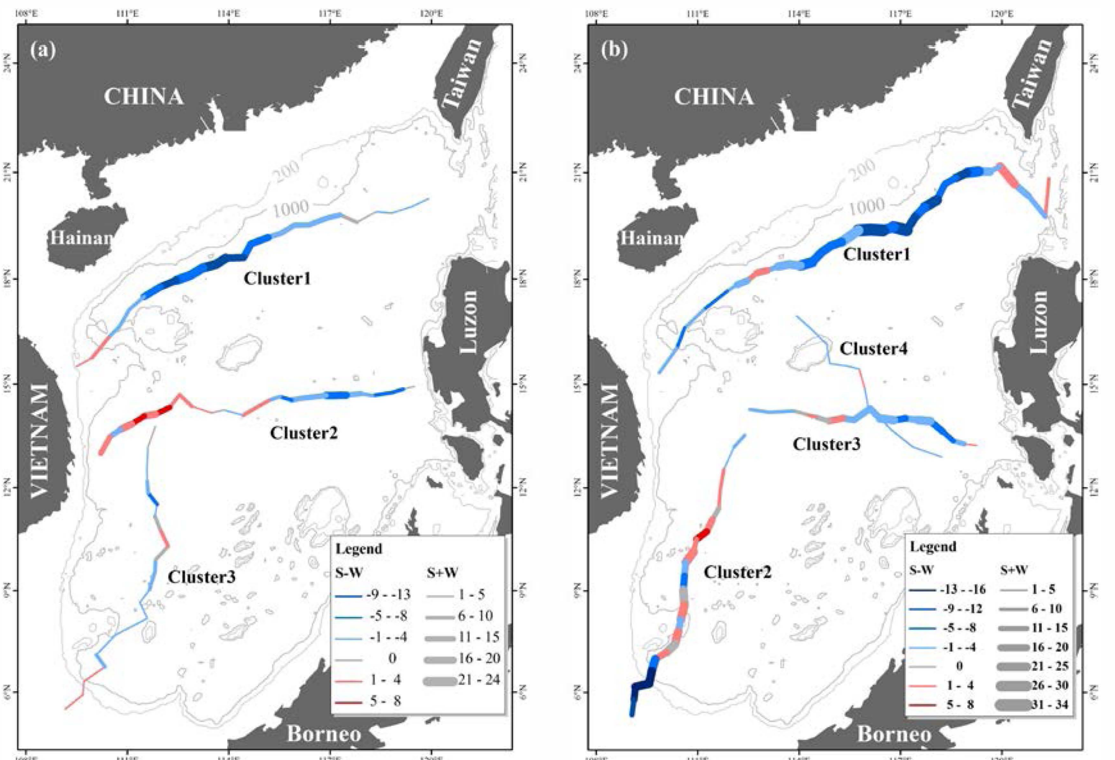

Figure 3. Temporal characteristics of eddies moving patterns: (a) anticyclonic eddies; (b) cyclonic eddies. The color of line indicates the dominated monsoon. It is calculated using the number of summer minus the number of winter; the positive means summer monsoon (red lines), and the negative means winter monsoon (blue lines). The width of line reflects the representativeness of this segment. It is calculated using the number of summer plus the number of winter. The contour lines are 200m and 1000m isobaths.

C. *Temporal Analysis*

According to the temporal analysis method described in Part Ⅱ B, we tred to find the temporal characteristics of representative routes identified in Part Ⅲ B. Affected by the monsoon, summer in the SCS is from May to October, while winter is from November to April. In our experiment of temporal analysis, for every segment of representative trajectories, we calculated the projection time span of all participated line segments simplified from original trajectories, and then transferred it to the summer/winter monsoon. We counted the number of summer and winter monsoon respectively, chose the dominated monsoon as the time attribute of this segment, and visualized this result.

The temporal analysis results illustrated that heterogeneity of the dominant time span existed in the movement of ocean eddies. They do not exist permanently but show significant seasonal variations. In the northern SCS, eddies moving paths mainly existed in winter; anticyclonic eddies finally disappeared in summer, and the temporal attribute changed gradually and continuously (Fig. 3a); while cyclonic eddies may have originated in summer, and the temporal attribute changed randomly (Fig. 3b). This random change suggested that representative trajectory should be divided and trajectories in this cluster may be not similar with others in the time dimension. The representative routes marked Cluster2 in Fig. 3b shows this phenomenon typically. The temporal attribute of this trajectory changed constantly. Therefore, few cyclonic eddies moved from the east of central Vietnam all the way to the southern SCS. Observation data also verifies that eddies mainly move circularly here instead of moving in one direction [17]. There is another interesting type of route displayed by the trajectory marked Cluster2 in Fig. 3a. In this pattern, eddies originated west of Luzon in winter, propagated westward, and disappeared offshore of central Vietnam in summer. The temporal attribute changed gradually, but the representativeness first decreased and then increased. We could infer that some anticyclonic eddies originated from west of Luzon in winter and may have disappeared in the center; then some originated from the center in summer and were continuously moving westward.

IV. CONCLUSION

This paper proposed an analysis approach to exploring underlying temporal characteristics of large trajectory datasets. It first adopts the partition-and-group framework [6] to identify partial moving patterns, and then calculated the dominant time span of each segment of the representative routes to reveal the dynamics of moving objects.

We applied this method to studying the ocean eddies in the SCS during 1992-2012. Analysis of 816 strong eddies which traveled a long distance showed that anticyclonic and cyclonic eddies have a common moving path along the northern continent slope of the SCS and temporal feature of the path indicated that most eddies travel during the winter monsoon. Also, heterogeneity of the dominant time span along the traveling path to some extent reflects the temporal variations of eddy moving patterns. The analysis results not only confirmed the method utility but also provided new insights into understanding the dynamics of ocean eddies in the SCS.

Although we explored the temporal characteristics of moving patterns, the spatial and temporal analysis are not integrated. Some representative trajectories may be changed if time constraint were added in clustering algorithm. Therefore our future studies will focus won incorporating temporal information into trajectory clustering procedure and take temporal continuance into consideration.

REFERENCES

[1] Y. Sadahiro, R. Lay, and T. Kobayashi, "Trajectories of Moving Objects on a Network: Detection of Similarities, Visualization of Relations, and Classification of Trajectories," Transactions in GIS, vol. 17, pp. 18-40, 2013.

[2] S. J. Camargo, A. Robertson, S. Gaffney, and P. Smyth, "Cluster analysis of western North Pacific tropical cyclone tracks," in Proceedings of the 26th conference on hurricanes and tropical meteorology, 2004, pp. 250-251.

[3] P. Kalnis, N. Mamoulis, and S. Bakiras, "On discovering moving clusters in spatio-temporal data," in Advances in spatial and temporal databases, ed: Springer, 2005, pp. 364-381.

[4] M. Andersson, J. Gudmundsson, P. Laube, and T. Wolle, "Reporting leadership patterns among trajectories," in Proceedings of the 2007 ACM symposium on Applied computing, 2007, pp. 3-7.

[5] J. McIntosh and M. Yuan, "Assessing similarity of geographic processes and events," Transactions in GIS, vol. 9, pp. 223-245, 2005.

[6] M. Nanni and D. Pedreschi, "Time-focused clustering of trajectories of moving objects," Journal of Intelligent Information Systems, vol. 27, pp. 267-289, 2006.

[7] J.-G. Lee, J. Han, and K.-Y. Whang, "Trajectory clustering: a partition-and-group framework," in Proceedings of the 2007 ACM SIGMOD international conference on Management of data, 2007, pp. 593-604.

[8] D. B. Chelton, P. Gaube, M. G. Schlax, J. J. Early, and R. M. Samelson, "The Influence of Nonlinear Mesoscale Eddies on Near-Surface Oceanic Chlorophyll," Science, vol. 334, pp. 328-332, 2011.

[9] D. B. Chelton, M. G. Schlax, and R. M. Samelson, "Global observations of nonlinear mesoscale eddies," Progress in Oceanography, vol. 91, pp. 167-216, 2011.

[10] J. C. McWilliams, "The Nature and Consequences of Oceanic Eddies," in Ocean Modeling in an Eddying Regime, ed: American Geophysical Union, 2013, pp. 5-15.

[11] J. Yi, Y. Du, Z. He, and C. Zhou, "Enhancing the accuracy of automatic eddy detection and the capability of recognizing the multi-core structures from maps of sea level anomaly," Ocean Science, vol. 10, pp. 39-48, 2014.

[12] J. Yi, Y. Du, F. Liang, C. Zhou, D. Wu, and Y. Mo, "A representation framework for studying spatiotemporal changes and interactions of dynamic geographic phenomena," International Journal of Geographical Information Science, vol. 28, pp. 1010-1027, 2014.

[13] W. Zhuang, Y. Du, D. Wang, Q. Xie, and S. Xie, Pathways of mesoscale variability in the South China Sea vol. 28. Heidelberg, ALLEMAGNE: Springer, 2010.

[14] G. Wang, J. Su, and P. C. Chu, "Mesoscale eddies in the South China Sea observed with altimeter data," Geophysical Research Letters, vol. 30, p. 2121, 2003.

[15] K. K. Liu, S. Y. Chao, P. T. Shaw, G. C. Gong, C. C. Chen, and T. Y. Tang, "Monsoon-forced chlorophyll distribution and primary production in the South China Sea: observations and a numerical study," Deep Sea Research Part I: Oceanographic Research Papers, vol. 49, pp. 1387-1412, 2002.

[16] P. Xiu, F. Chai, L. Shi, H. Xue, and Y. Chao, "A census of eddy activities in the South China Sea during 1993–2007," Journal of Geophysical Research, vol. 115, 2010.

[17] G. Wang, D. Chen, and J. Su, "Generation and life cycle of the dipole in the South China Sea summer circulation," Journal of Geophysical Research, vol. 111, p. C06002, 2006