Online Tracking and Summarization over Streaming Maritime Trajectories*

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Abstract. In this work, we are focusing on efficient management and processing of streaming traces from ships sailing in the open sea. We address issues concerning evolving trajectories generated by such massive positional updates. We advocate that a close synergy between inherent spatiotemporal properties and the stream processing paradigm can provide a solid framework for intelligent online tracking. In contrast to other related works on this topic, this approach attempts to strike a balance between the necessity for real-time monitoring of numerous objects, while also retaining salient features along their recent motion history. As our evaluation indicates, maritime datasets can serve as an excellent case study for detecting mobility trends from streaming trajectories.

1 Motivation

Many modern monitoring applications collect and analyze huge amounts of flowing, uncertain and heterogeneous spatiotemporal information. Typical examples include location-based services for tourism or advertising, platforms for traffic surveillance or fleet management, notification systems for natural resources and hazards etc. Our particular interest is on managing spatiotemporal data relayed from ships sailing in the sea, not only in terms of their actual whereabouts, but also regarding their evolving trajectories across time. How such fluctuating, transient, and possibly noisy positional streams can be processed *online* is the topic of this study, assuming a large number of ships in a given area of interest.

Our first objective is to track *significant changes* in each vessel's course so as to instantly identify "critical points", e.g., indicating a stop, a sudden turn, or slow motion. Thus, we may easily characterize in real time the current motion of each monitored ship with a particular annotation. Of course, such derived features can be used for map display, but they are mostly valuable in emergency situations, e.g., issuing an alert when a passenger ship has stopped unexpectedly in the open sea, just in case this event required a rescue operation.

Moreover, we would like to take advantage of those online annotations and retain lightweight, succinct *synopses* of maritime trajectories over the recent

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past. Except for harsh weather conditions, traffic regulations, local manoeuvres etc., ships normally follow almost straight, predictable routes. It turns out that a large amount of raw positional updates could be suppressed with minimal losses in accuracy, as they hardly contribute additional knowledge about maritime motion patterns. Instead of resorting to a costly simplification algorithm, we opt to reconstruct vessel traces *approximately* from already available critical points. This summarization should be triggered automatically according to the type of detected motion features, so as to refresh each compressed trajectory accordingly.

2 Stream-based Processing Framework

Setting. We assume a centralized processor that accepts positional messages from a large number N of location-aware vessels. All messages are timestamped according to a global clock at distinct instants τ (e.g., seconds), so they get ordered by their timestamp values. Every vessel o relays to the server its current geographic position p, e.g., a pair of longitude and latitude coordinates. Updates may be sent over at irregular intervals, e.g., when an object has gone far away from its previously known position or upon significant change at its speed. Each vessel may specify its own frequency of positional messages, yet we assume that it must report at least once every T time units (e.g., 10 minutes), otherwise its current itinerary is finished (i.e., it has stopped). So, until further notice, the server knows nothing but the latest (x, y) coordinates of a given ship o, and assumes that o is found somewhere along its predicted route. For the supplied AIS dataset in Brest area, an *in-memory processing* framework was developed in C++, without making use of any database platform or spatiotemporal indexing.

Mobility Tracking. The algorithm accepts fresh positional tuples like $\langle o, x, y, \tau \rangle$ and applies several parametrized methods in order to identify critical points. It first computes instantaneous velocity vector $\overrightarrow{v}_{now}$ per ship o, from its two most recent positions. Then, the server can instantly deduce a variety of indications:

- *stop*: It signifies whether the vessel is actually moving or has stopped, by specifying a suitable threshold v_{min}, e.g., if speed is less than 1 knot.
- *speed change*, when current value v_{now} deviates by more than a percentage parameter α from the previously observed v_{prev}. With a formula like $|\frac{v_{now}-v_{prev}}{v_{now}}| > \alpha$, it can be derived whether a ship accelerates or decelerates.
- *turn*: It occurs when direction has changed by more than a given value $\Delta\theta$, e.g., there is a difference of more than 10 degrees from its previous heading.
- *gap* in reporting is issued when a vessel has not emitted a message for a period T, e.g., at least 10 minutes ago.

In addition to such features (actually, each is a continuous query), this scheme can collect spatiotemporal measurements and detect longer-term changes like:

- *traveled distance*: By specifying a given position as the starting point of an itinerary, this utility can accumulate Euclidean distance between successive locations and continuously provide the current distance from its origin.

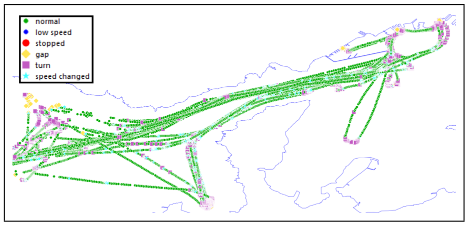

Fig. 1. Instantaneous characterization.

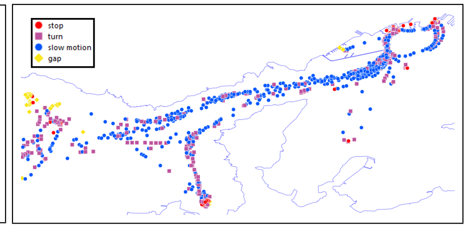

Fig. 2. Data reduction to critical points.

– *slow motion*: By setting a threshold v_{low} for low speed (e.g., 5 knots), we can identify if a vessel moves slowly during the past m successive observations.
– *smooth turns*: In this case, it is found that the ship turns slowly, by checking if its heading changes slightly towards a new direction at each positional update. As soon as the accumulated changes in heading exceed a threshold of $\Delta\theta$ degrees, the median of these involved positions is characterized as a turn. Then, checking for smooth turns starts again from scratch. This phenomenon disappears as soon as subsequent headings are no longer deviating.
– *long-term stops*: If a sufficient number m of consecutive stop indications has been detected until now, then this ship has remained idle. To identify such an event, all stops must be found within a radius r, e.g., 200m, depending on maritime drifts and inherent positional error. Such a filtering is indispensable in order to get rid of noise, e.g., when consecutive locations indicate slight displacements back and forth, while the ship remains stationary in the dock.

As a result of this online processing, *critical points* may be emitted as soon as one of the following instantaneous or longer-term phenomena gets detected: *turn, gap, slow motion, smooth turn, long-term stops*. Figure 1 illustrates original positions, whereas Fig. 2 depicts only those classified as critical points. Evidently, these latter locations have been chosen with spatiotemporal criteria, and practically amount to just a small subset of the raw positions. The rest simply indicate a normal behavior according to the known velocity vector of the ship, and could have been shed or not relayed at all without significant loss of information. As our preliminary investigation indicates, this method has been able to achieve more than 98% compression ratio for typical movements in this area.

Summarization. Indeed, critical points can offer all the essential information about current and recent movement of each vessel. By compiling these points in chronological order, this scheme can readily reconstruct an approximate, yet quite reliable trajectory of any ship, as Fig. 2 clearly depicts. In contrast to other line simplification [1,2,3] or sampling algorithms [4] over moving objects and trajectories, our approach typically requires a single scan at cost $O(1)$ per incoming point, as it does not need to look back at the entire history of movement. Only when detecting long-term stops or slow motion the cost is $O(m)$, but m is a small number of buffered recent features with common characteristics per ship. It may not be guaranteed that the resulting path is as accurate as the one de-

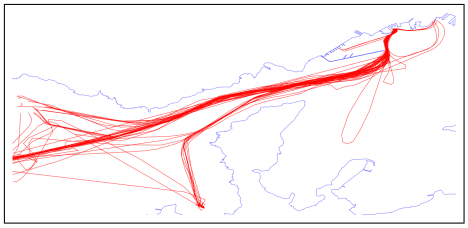

Fig. 3. Compressed trajectories.

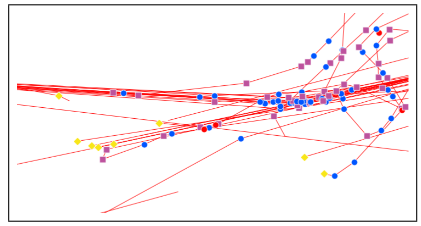

Fig. 4. Disconnected segments.

rived by an offline generalization technique; the latter examines larger segments and judiciously selects points with minimal error, but our method is certainly faster and achieves high compression rates with tolerable approximation quality.

Visualization. Maps are a precious tool when exploring abnormal behaviors in maritime applications, as well as for verification of trajectory synopses. So, an additional utility allows processed results to be periodically exported into KML files for map display, involving not only critical points, but also compressed routes (Fig. 3). For some vessels, these timestamped polylines (time instants are the third dimension in coordinates) may have *discontinuities* in case of temporal gaps or long-term stops (Fig. 4), thus enabling detection of distinct itineraries.

3 Outlook

Overall, this single-pass methodology has shown powerful capabilities to capture interesting phenomena from streaming trajectories in a maritime context. Next, we plan to conduct a comprehensive assessment of these sampling techniques in order to estimate the error induced (i.e., deviation from original traces), as well as an empirical performance study. Processing with a sliding window model could certainly offer important benefits, as more reliable velocity vectors may be estimated based on recent motion and not just instantaneous features. Moreover, the data reduction process could also integrate qualitative features (e.g. decision points in navigation) for advanced refinement. Last, but not least, this framework might have broader applicability to other types of continuously moving objects, like GPS-enabled vehicles, animals, RFID-aware merchandise etc.

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