

Techniques for interactive visual examination of autonomous vessel performance

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ABSTRACT

Autonomous vessel technologies are tested in the field on smaller test-bed platforms, often referred to as sea drones, which are widely used in a variety of applications and conditions. Development of models with desired capabilities and improved performance characteristics necessitates iterative testing followed by detailed examination of collected data. The data usually consist of time-stamped records including vessel positions and associated measurements. These records form vessel trajectories. Using an example dataset, we delve into different aspects of autonomous vessel functionality that developers may wish to analyse. Employing various visual displays, interaction techniques, and basic computations, we investigate these aspects to provide insights into system performance. We conclude by proposing a set of exploratory techniques aimed at aiding system developers in evaluating the performance of their devices.

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The source code, data, and/or other artifacts have been made available at <http://www.geoanalytics.net>.

1 INTRODUCTION

In recent years, we see an increasing trend of using remotely operated, autonomous or semi autonomous vessels, in diverse applications, ranging from marine research to environmental monitoring

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[9] and maritime logistics [7]. These complex systems are initially deployed on smaller boats (commonly referred to as sea drones), used as test-beds for the technology. While industrially produced sea drones are readily available on the market, specialised devices are often required for research and educational purposes [4]. Designers and developers of such devices need to test them repeatedly and analyse collected data to see whether the vessel performs as desired, identify problems, and determine necessary adjustments. Detailed analysis cannot be done without appropriate visualisation of test data exposing different facets of drone movement and operation in spatial and temporal contexts. Often test datasets produced are huge in volume, produced from several on board sensors, while the analysis is time critical (e.g. divert away from danger). The level of autonomy of these drones ranges from remote control to complete autonomy, requiring only an operators intervention in emergencies (hand-off-the-sticks). Drones designed for sea navigation have some distinct characteristics to be considered during analysis of their trajectories. More precisely, mobility data from surface drones refer to two-dimensional movement. These drones are only limited in their movement from the coastline or the presence of in-water obstacles, and are not confined from a road-like network. Moreover, the effect of the weather conditions is of high importance in maritime operations, especially when compared with in-land movement. External forces, like waves or currents, can easily manipulate the drones' movement and result in otherwise unexplainable behaviour between consecutive messages. In this paper, we propose interactive visual techniques designed to support diverse analysis tasks of sea drone developers.

The tasks include:

- Investigate movement characteristics and sensor measurement recordings from a single boat in space and time. This includes detection of anomalies and unwanted behaviours, such as boat malfunctions or weather-related disruptions of its movement.
- Assess the degree of stability in performing repeated movements and/or operations.

- Detect and examine potential collision situations, in particular, during simultaneous movement of several vessels.

Respectively, we consider major data exploration and analysis tasks, namely exploration of single trajectories, analysis of repeated parts of movement, and analysis of collective movement. For each of the tasks, we propose visual analytics approaches and identify relevant data quality issues.

The following sections are organized as follows. First, we provide an overview of related works regarding drone data and spatio-temporal data visualisations. Then, we describe the available data set and demonstrate how such data can be analysed. In the end, we conclude with a summary of techniques necessary for supporting data analysis, identifying gaps in coverage by the existing publicly available tools.

2 RELATED WORK

The work in [5] highlights a critical gap in the domain of drone technology and robotics, emphasising the absence of visual analytics tools for effective analysis of multidimensional spatio-temporal data. In essence, this deficiency poses significant challenges to users seeking to monitor, comprehend, and control the behaviours of individual drones and drone fleets. Analysis tools should facilitate exploration and analysis of drone telemetry, trajectory data, environmental variables, and other kinds of information, thereby enabling users to gain actionable insights into drone functioning.

Drones are produced by various companies, each employing proprietary tools and data formats that lack compatibility, making data sharing challenging. Consequently, competitions such as autonomous boat race [12, 14] serve as valuable platforms for gathering real-world datasets due to the limited availability of such data from proprietary sources.

Drone data consist of sequences of time-stamped geographic positions in 2D or 3D, annotated with measured attributes such as speed and direction, as well as characteristics of the moving object (e.g. weight or fuel consumption) and characteristics of the environment (e.g. wind speed and direction, water current attributes etc.) Such data are typical for mobility data science [10] and visual analytics of movement [1], with variety of analysis methods proposed in the literature. A framework for assessment of movement data quality was proposed in [2] and implemented as a protocol in a form of a Python library [6]. The protocol addresses missing data, precision, consistency, and accuracy problems in respect to spatial, temporal, and attributive data components on the level of elementary data records, intermediate segments of trajectories, and overall trajectories and sets of them.

3 THE AEGEAN RACE DATA

The 1st Aegean RoBoat Race (Autonomous Robotic Vessels Competition) took place in the island of Syros (Greece) in July 2022 [12]. The university-level competition was organised by the Intelligent Transportation Systems laboratory of the University of the Aegean and aimed to promote innovative ideas for smart shipping technologies. The student teams designed and developed autonomous robotic vessels on their own [13]. They competed, under real sea conditions, in speed, endurance and obstacle avoidance challenges,

where their vessels had to operate completely autonomously without any interference by the users. Similar to a sailing regatta, the first challenge had vessels to perform a single round trip, bounded by three buoys, thus testing their speed capabilities on short, predefined trips. The second, collision avoidance, aimed to demonstrate the ability of the vehicles to detect, and effectively avoid, obstacles on their path, including other moving vessels or static objects (scattered buoys). Finally, the third challenge focused on the endurance of the vessel and its systems for voyages of longer duration. For this purpose, a round trip between two buoys was followed, with vessels performing as many laps as possible in the extended time frame, without stopping. The resulting data set consists of positional and mobility data of 3 vessels during all 3 challenges (Table 1).

Table 1: The features of the extracted race data set and the number of positions for each challenge.

Feature	Description	Units
Identifier	Including the vessel’s team name, the challenge in question and a unique increasing number	
Timestamp	Reported time of each positional message	UNIX epoch format in seconds
Coordinates	Reported longitude and latitude of each message	EPSG: 4326
Speed	Reported speed of the vehicle at each point	kilometers per hour (kph)
Heading	Reported heading of the vessel’s bow	degrees (0-360)
		Challenge
	Speed	987
	Avoidance	1871
	Endurance	4071
	Total	6929

The data set has high temporal precision, with positions recorded almost every second (Figure 1 shows an example trajectory), resulting in over 6900 positional reports (Table 1). However, using GPS coordinates with only 7 decimal points lacks the precision needed to accurately track movement in small areas when recording data at a temporal resolution of about 1 second. This limitation can lead to distortions on maps, such as checkerboard-like patterns, and sudden fluctuations in derived movement metrics like speed, acceleration, direction, and turns.

4 EXPLORATION OF A SINGLE TRAJECTORY

Possible objectives of a detailed exploration of a single trajectory include inspection of the characteristics of the movement, position recording, and measurements. The most common visualisation of trajectories is by lines on a map, as in Fig. 2, left. An animated map can show the progress of the movement over time but not the overall shape of the trajectory. A space-time cube [8], as in Fig. 2, right, shows the relative times of different segments of the



Figure 1: Analysis of the regularity of the position recording. The lengths of the time intervals between the recorded positions are represented by proportional sizes of circle symbols. The largest circle correspond to a time gap of 23 seconds, whereas the regular interval length is 1 second.

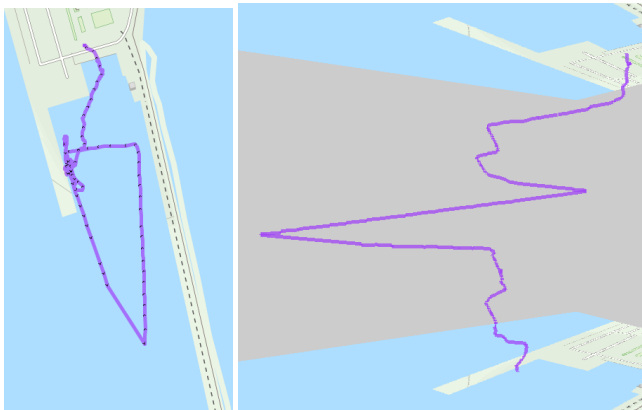


Figure 2: A single trajectory represented on a map (left) and in a space-time cube (right). The time axis in the space-time cube is oriented upwards.

trajectory, as well as the movement directions and speeds. The speed in a trajectory segment is indicated by the inclination of the corresponding line: the smaller the inclination, the higher the speed.

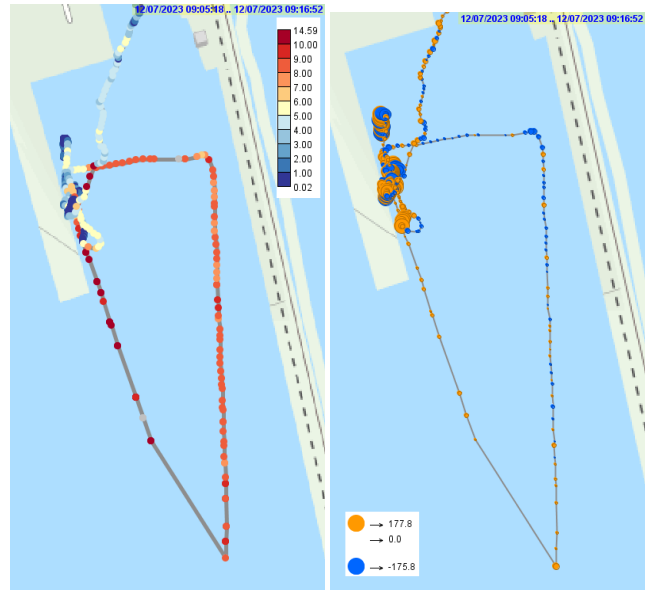


Figure 3: Exploration of movement characteristics. Left: speed measurements are represented by point colouring. Right: deviations of the movement direction (computed from consecutive positions) from the vessel heading (recorded during the movement) are represented by proportional sizes and colours of circle symbols. Orange symbolises deviations to the right and blue to the left.

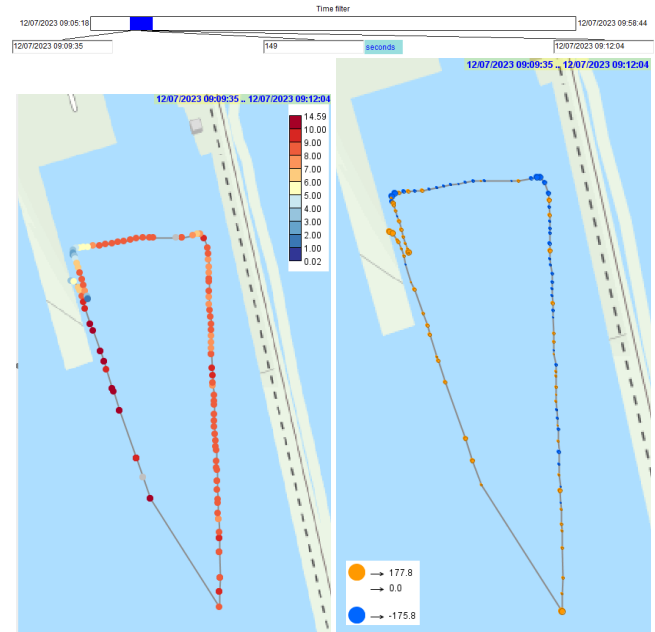


Figure 4: Selection of a relevant part of the trajectory by means of temporal filtering,

To explore the details of the position recording and sensor measurements, it is useful to combine the representation of the trajectory by a line with representing the recorded points by symbols, such as dots. Sizes and/or colours of the symbols can encode recorded measurements, as, for example, the speed in Fig. 3, left, or computed variables, such as the time to the next point in Fig. 1. The positions of the point symbols on a trajectory line indicate gaps in measurements and reveal line segments resulting from interpolation between known positions. Such estimations may significantly differ from the unknown actual path.

Visualisation of speed and course data along a trajectory can also give a hint about the impacts of wind and waves on the vessel movement. Thus, we see on the map on the left of Fig. 3 that the speed of the southward movement was notably higher than in the movement to the north, which shows the impact of the wind blowing from the north and northeast. The impact of the wind on the vessel course can be explored by calculating and visualising the differences between the recorded vessel heading and the movement course computed from consecutive vessel positions. On the right of Fig. 3, the deviations are represented by dot symbols with the colour (blue or orange) encoding the direction of the deviation (left or right of the heading) and size proportional to the amount of the deviation, in degrees.

A necessary tool for interactive exploration of trajectory data is time filter allowing selection of time intervals for viewing only data generated in these intervals while the remaining data are hidden. The work of a time filter is illustrated in Fig. 4, where it was used to hide irrelevant parts of the trajectory that reflect the vessel movements before and after the race. The filter was applied to the data presented in Fig. 3. We see that the speed during the race was mostly quite high and the deviations of the course from the heading were low compared to the hidden parts of the trajectory that were visible in Fig. 3. Still, the orange and blue colours of the dot symbols signify the impact of the northern and northeastern wind: the course slightly deviated to the right of the heading during the southward movement and to the left during the northward and westward movements.

In a similar way, one can explore any sensor measurements taken by the vessel along the route. To summarise, basic techniques for visual exploration of individual trajectories and associated point-based measurements include representation of the trajectories by lines on a map and in a space-time cube, using point symbols for showing the locations of the recorded trajectory points and any attributes associated with the points, and time filter for selection of time intervals and corresponding trajectory parts to focus on.

5 EXPLORATION OF REPEATED MOVEMENT

During development and testing, drones often need to perform repeated tasks, following the same pre-defined route. Some variations of the route may occur due to changes in context such as weather conditions, activities of the drone itself, other events that happened nearby (e.g. proximity to stationary obstacles or other moving objects) etc. Examples of such data have been collected during the so-called endurance race, see Figure 5. Similarly to Figure 2, the space-time cube in the middle shows dynamics of the 3 trajectories.

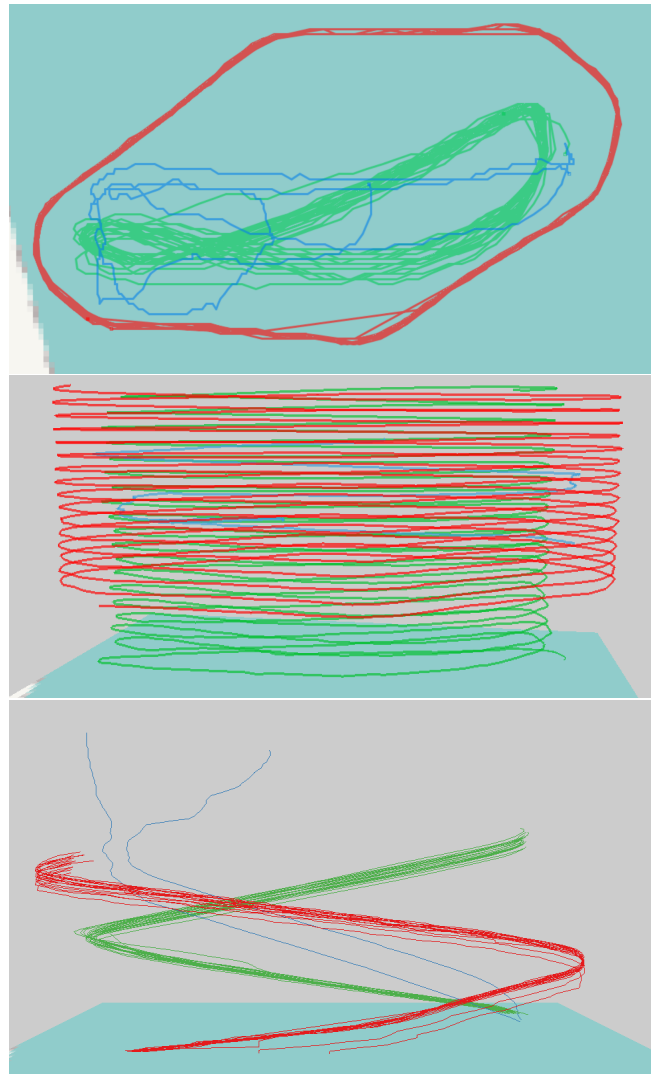


Figure 5: Endurance race: trajectories of the 3 drones on the map (top) and map space-time cube (middle and bottom).

In the bottom, trajectories are divided into repeated fragments and their starting times are aligned.

Analysis of repeated movement is not limited to purely spatial and spatio-temporal shape matching. In addition, it is necessary to study the dynamics of attributes for the whole trajectories and their dynamics within the trajectories. Thus, by computing average speeds over multiple fragments we observed gradual speed decrease over the sequence of loops for each drone, indicating their degrading performance. More detailed analysis can be done using time series displays, as shown in Figure 6. Such displays are suitable for understanding the overall dynamics of movement in the repeated fragments and for identifying times and locations of speed changes, as well as sporadic fluctuations. In further analysis, these patterns can be matched to context data (e.g. weather attributes) or events of proximity to stationary obstacles or other vessels.

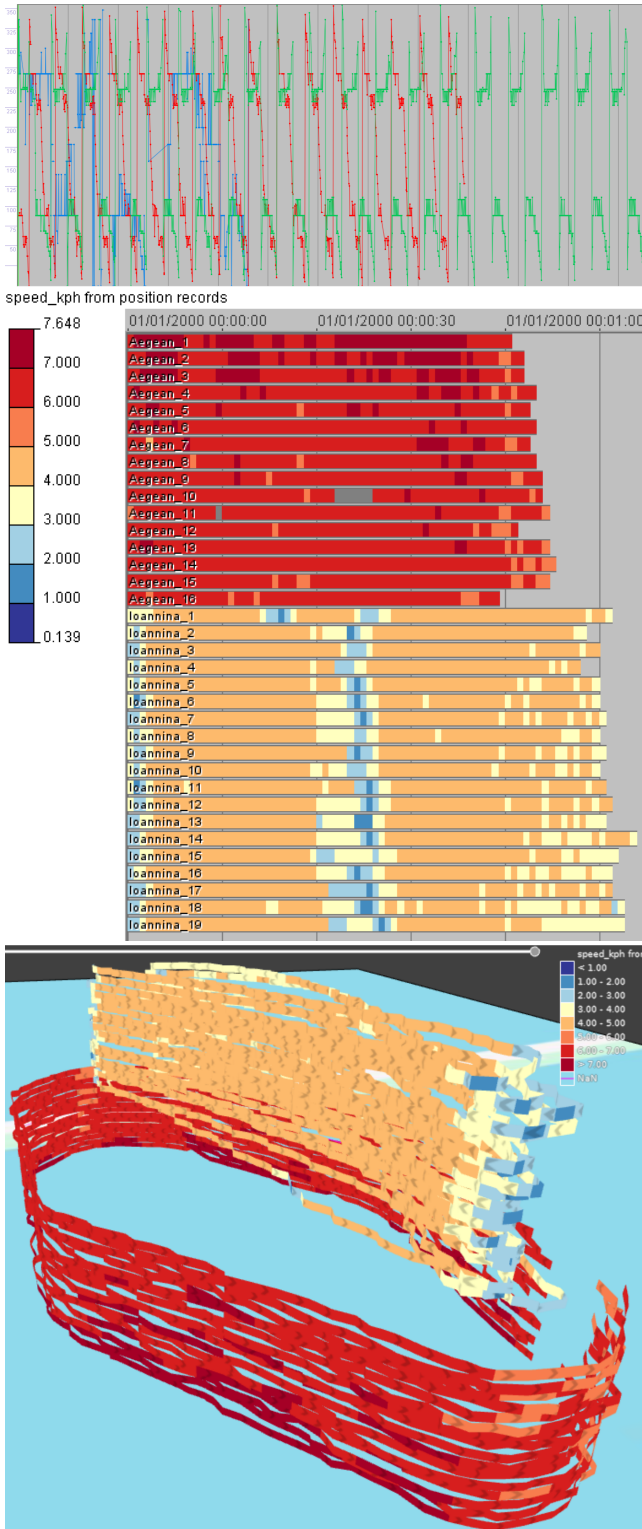


Figure 6: Endurance race: dynamics of speeds over multiple loops. The display on top shows dynamics over time; segmented time bars in the middle align starts of all loops; trajectory wall display [3] in the bottom shows speeds in their spatial context.

6 EXPLORATION OF INTERACTIONS

Here we focus on the task of detecting and exploring events of close approach of vessels to other static or moving objects; we shall call such events *interactions* [11]. Interactions can be detected by computing the minimal distance from each point of a vessel trajectory to the boundary or location of another object at the time of attaining this point.

In computing the distance to a moving object, it is necessary to take into account the possible differences between the time moments when the locations of the given vessel and the other object were sampled. Thus, for a vessel position measured and recorded at time moment t there may be no position in the trajectory of another moving object having exactly the same time reference. Therefore, in computing the distances, it is necessary to take a temporal buffer $[t - \epsilon, t + \epsilon]$ around each position of the vessel trajectory, find the points from the other trajectory where times fit in this time interval, and compute the distances to all these points. The temporal threshold ϵ is chosen based on the coarsest temporal resolution of the position recording among all trajectories involved in the calculation.

To detect close approaches, it is also necessary to define what distance between objects can be treated as a close approach, i.e., to set a distance threshold δ . It is chosen depending on the sizes of the vessel and the objects that can be approached during the vessel movement.

As an example, we show results of detecting interactions between two autonomous vessels during a race using the threshold settings $\epsilon = 5$ seconds and $\delta = 1$ m.

Exploration of detected interactions requires them to be represented visually on a map, as, for example, in the middle of Fig.7. The points of close approach are marked by dot symbols and connected to the corresponding points from the other trajectory by lines. Another visual representation is a space-time cube, as in the lower part of Fig.7. It shows the approximate relative times of different interactions.

However, occlusions and line intersections in both the map and the cube complicate the examination of the details of the interactions. This problem can be solved using time filtering, as illustrated in Fig. 8. For convenience, a time interval containing one interaction can be selected using a mouse operation within the map display.

7 DISCUSSION

By considering the example data set of the Aegean boat race, we formulated analysis tasks that are necessary to address during the development and testing of autonomous vessels. To support these tasks, the following computational and visual techniques are necessary.

- General infrastructure:
 - Basic tools for composing trajectories from sequences of time-stamped positions, calculation of derived attributes such as point-wise distances, speeds, time lags etc.
 - Tools for assessing data properties, including identification of omissions (e.g. long intervals between successive points), errors in positions and measurements, and outliers, as proposed in [2, 6].

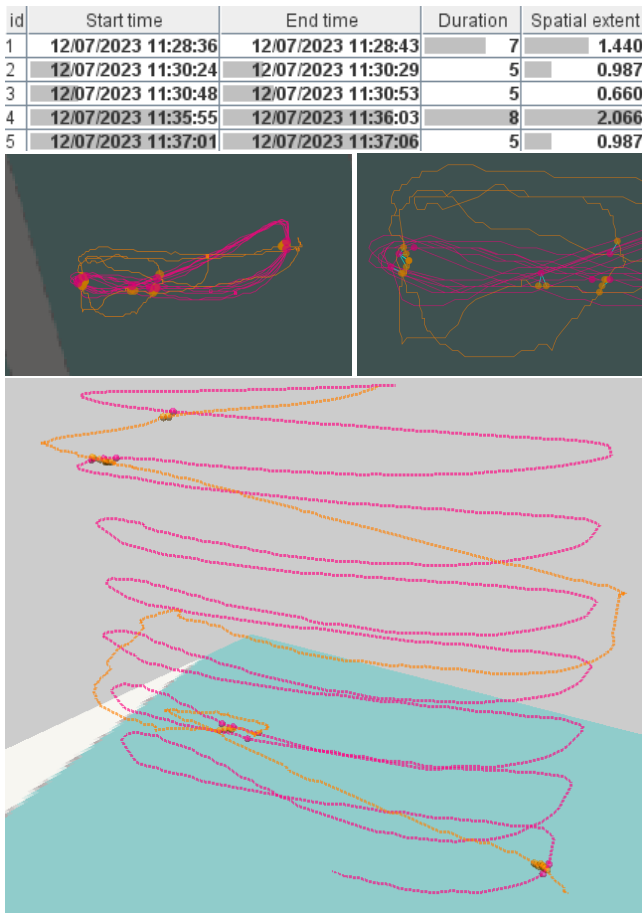


Figure 7: Interactions between two autonomous vessels during a race. Top: a table describing the detected interactions. Middle: points of close approach are marked on a map. An enlarged map fragment is shown on the right. Bottom: the trajectories and points of close approach are displayed in a space-time cube.

- Control of consistency of sampling rates and spatial resolution through histograms.
- Temporal filtering tools enabling focused exploration of data subsets from selected time intervals.
- Analysing single trajectories:
 - Tools supporting analysis of trajectory attributes e.g. on time graphs.
 - Visual representation of trajectories and point-related attributes on maps and in a space-time cube.
- Analysing repeated fragments of trajectories:
 - Tools for dividing trajectories into repeated fragments, including interactive (e.g. selection of division points or areas) and computational (e.g. calculation of distance to the selected points) techniques.
 - Calculation of aggregated characteristics of fragments (duration, speed, etc.; average values and indicators of

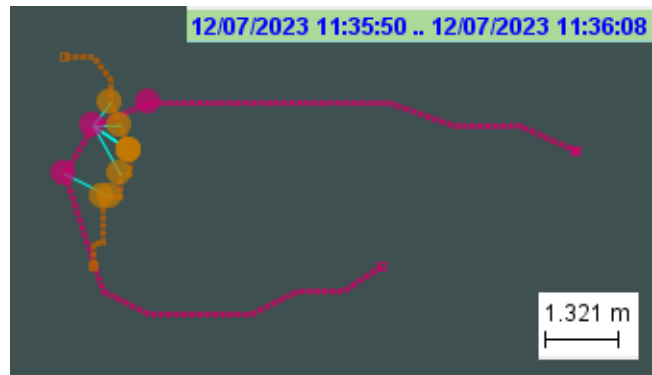


Figure 8: One interaction has been selected for inspection by means of time filtering,

variation) and visual tools for their analysis (e.g. bar charts, tabular representations).

- Analysing interactions:
 - Computational detection of interactions within given spatial and temporal thresholds.
 - Visual representation of interactions in space (map), time (time line) and space-time (space-time cube), with a possibility to get an overview and then access details on demand.

Some of the listed techniques are available in open-source implementations such as the protocol for identifying problems in continuous movement data [6], while others exist only in proprietary research prototypes (e.g. in V-Analytics [1]) and are difficult to access. Extension of open-source libraries is a challenge that needs to be addressed for supporting development of autonomous vessels. There are several complications that may prevent easy integration of required methods:

- While some of the techniques can be effectively used in static or low-interaction modes, others such as space-time cube require interactivity which is hardly accessible in Python implementations.
- In addition to analysis of earlier collected data, streaming settings pose further challenges to implementations.

8 CONCLUSION AND FUTURE WORK

This work described some of the preliminary steps into the exploratory analysis techniques aimed at supporting sea drone operators and developers in evaluating and understanding the performance of their systems. As the focus moves towards the operator side and the design of decision support tools that can support real time decision making and awareness, the big data challenges are several orders of magnitude more complex. Future work will be focused on analysis such data in large to support the decision maker (operator) in critical situations.

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