Interactive Poster: Visualization of vessel trajectories for maritime safety and security systems

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Abstract

We present a method to compute and visualize behavioral patterns of trajectories by means of density. The computational model is a skeletal convolution approach, which smoothes continuous trajectories to find trends in normal behavior. Our method is to be applied in the maritime domain to establish safety and security by coastal surveillance systems.

Keywords: AIS, GPS, maritime, trajectory visualization.

Index Terms: I.3.3 [Computer Graphics]: Picture/Image generation—Line and curve generation.

1 Context

The sea seems an open playground, but regulations hold, and furthermore, safety (collision prevention) and security (thread prevention) need to be ensured. Operators monitor the coast using a Maritime Safety and Security (MSS) system, which allows analysis of multiple heterogeneous data sources. We aim at visualization methods with feedback to support operators to react on dangerous situations. To detect abnormal behavior, it has to be known what normal behavior is. As a first step, we start with visual exploration of trajectories of large vessels.

Recently, professional vessels are obliged to be equipped with an advanced GPS tracker: Automatic Identification System (AIS) [2]. An AIS publicly broadcasts the status of a vessel, initially to prevent collisions between vessels. For behavioral analysis, a network of base stations has been setup to collect all broadcasted messages. Messages contain vessel information (e.g., identification numbers, name and ship dimensions) and voyage plans (e.g., destination, expected time of arrival, draught and type of vessel). Furthermore, the actual movement (e.g., position, velocity, course) is broadcast up to every 2 seconds, depending on the velocity. These movement messages are the data points that we use as input. A typical day consists of 3 million messages (500MB) of nearly 1450 unique vessels.

Since vessels move slowly, and mainly in straight lines, we have lossy compressed the actual movement using line simplification [1], which is applied for both position and velocity dimensions. Using this approach, even with small errors (50m and 0.5knot), more than 95% of the data can be discarded. We present a visualization method based on continuous trajectories, which are approximated depending on the interpretation of the attribute by interpolating data points in either time or space.

2 Problem

Currently, coastal surveillance systems display only live data on a map by means of glyphs and text. With this approach, it is hard to observe whether a vessel moves normally or not. Our method enriches these situational displays with a context of normal behavior. We focus on the following aspects of normal behavior, without prior knowledge of regulated areas:

- Shipping lanes: where does the majority sail and what is the general course?
- Anchoring places: where do vessels drop anchor?

To estimate where the majority sails, trajectories during a period of time $[0,T]$ are assumed to be normal. These trajectories are displayed using a density plot as an overlay on a map. Density is the average spatial distribution of vessels during $[0,T]$. Trends are found using convolution, which smoothes the trajectories to avoids sampling artifacts. The general course and anchoring places are visualized by decorating the density plot.

For this kind of applications, density is usually computed by convolving independent data points [3]. However, a trajectory is continuous, hence between two data points a vessel does not contribute to the density where it should do (see figure 1 left). To convolve line segments, a skeletal convolution approach is more appropriate. Our method extends skeletal convolution by exploiting the broadcasted velocities to obtain a more realistic density, i.e., the contribution is high where a vessel sails slowly, and vice versa.

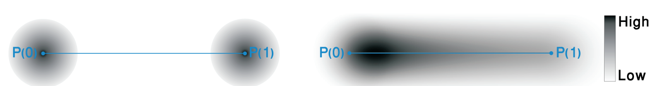

Figure 1: Partial trajectory between a slow and a fast data point. Left: point-based approach. Right: skeletal approach.

3 Method

Our method is composed of a density model (section 3.1) and a visualization model (section 3.2) to display normal behavior. In the final section, our method is exploited to present abnormal behavior.

3.1 Trajectory density model

Consider vessels V. A vessel $w \in V$ sails along a continuous trajectory $\mathbf{p}_w(t)$, with t in time interval $[0,T]$. For a point $\mathbf{q}$, the density $D_w(\mathbf{q})$ contributed by a trajectory of vessel w is

$$D_w(\mathbf{q}) = \frac{1}{T}\int_0^T k(|\mathbf{p}_w(t) - \mathbf{q}|)\mathrm{d}t. \tag{1}$$

Convolution is applied with an unit volume kernel k moving along the trajectory $\mathbf{p}_w(t)$, which distributes the relative presence of w to the neighborhood of $\mathbf{q}$ during $[0,T]$. The total density $D(\mathbf{q})$ of all vessels is the sum of the individual contributions

$$D(\mathbf{q}) = \sum_{w \in V} D_w(\mathbf{q}). \tag{2}$$

The right-hand side of figure 1 displays the densities of a partial trajectory between two data points, in which a vessel starts slowly in $\mathbf{p}(0)$ and accelerates to $\mathbf{p}(1)$. Convolution is applied with a fixed size cone kernel. By using a terrestrial unit, the radius r of the kernel k is an intuitive smoothing parameter.

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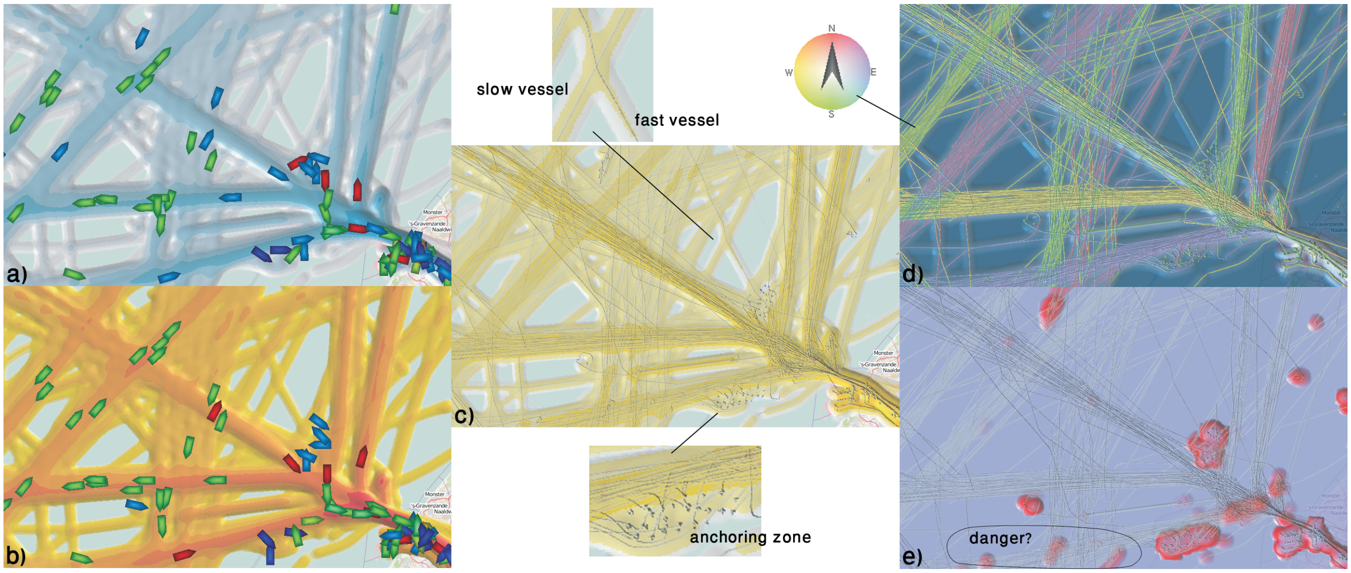

Figure 2: Multiple views of the entrance of Rotterdam harbor of one day, using various settings. All views are convolved using a cone kernel with $r_{total} = 1.5$km, $r_{small} = 0.1$km, $T = 1$ day, and use D_{total} with logarithmic scale. Live data of another day is plotted on figure a and b, where color encodes the type of the vessels. a) Canals of D_{total} using $\alpha = -3$. b) Ridges of D_{total} using $\alpha = 3$. c) Etching trajectories with $\alpha = -3$. At the top, solving ambiguity of density: a slow vessel has a high total density, whereas a fast vessel has a low total density. At the bottom, anchoring zones are visible by means of wells. d) Color coded course in etching trajectories using $\alpha = -3$. e) Presenting abnormal behavior: locations where a vessel moves less than four knots are highlighted. At the bottom, danger may occur since vessels move slowly in shipping lanes.

3.2 Visualization model

The total density D_{total} is visualized using two visual cues: color coding and geometry of a height field H. Between shipping lanes D_{total} may differ orders of magnitude. To emphasize less frequently used shipping lanes, optionally a logarithmic scale is used for D_{total}.

The height field H is

$$H(\mathbf{q}) = \alpha \cdot D_{total}(\mathbf{q}). \tag{3}$$

Canals can be taken as a metaphor to generate geometry when $\alpha < 0$: the more vessels sail in a canal the deeper it gets. Details are enhanced by scaling using α. The height field H is visualized using a basic light illumination, with one white light source aiming from the top right corner. In figure 2a, D_{total} is visualized with $\alpha = -3$ resulting in canals, where $\alpha = 3$ in figure 2b results in ridges. Live data on top of both images explain the usage of these density plots: none of the vessels are in thin density hinting for normally moving vessels.

The total density D_{total} is decorated with individual trajectories resulting in an overview+detail visualization (figure 2c). In order to do so, density D_{small} is computed with a small kernel. Only the geometry of H is manipulated by weighting the densities

$$H(\mathbf{q}) \quad = \quad \alpha \cdot D_{total}(\mathbf{q}) + \beta \cdot D_{small}(\mathbf{q}). \tag{4}$$

For negative β, trajectories etch the surface of D_{total}. This makes anchoring places visible, since stopping results in a well. If the image is used for detailed investigation, etching trajectories solve ambiguity of density: multiple fast vessels result in the same total density as a slow vessel. By comparing the total density with the number of etching trajectories, it is possible to conclude whether vessels have moved fast or slowly. By color coding the average course in the etching trajectories (figure 2d), the general course of shipping lanes becomes visible. Using a continuous rainbow color map along a wind rose, opposite directed lanes can always be distinguished due to pseudo-complementary colors.

3.3 Application

Our visualization method can also be used to highlight anomalies, since they occur at negligible parts of the map. We use simple rules like “velocity less than x knots” to define anomalies, where in the future machine learning will be used. The total density is only computed for those parts of trajectories that match the anomaly rules. In figure 2e, only parts of trajectories are convolved where a ship sails less than 4 knots. Density is displayed using a color map interpolating from blue to red and back, which creates space to display other anomalies. In the bottom center of figure 2e, vessels move slowly in shipping lanes hinting for dangerous situations.

4 Future Work

We will extend our visualization method by embedding more dimensions of data in various visual cues. Furthermore, our versatile visualization method is work in progress that needs exploration of optimal settings. The performance will be improved, for instance by searching for an analytical solution for equation (1). Finally, not all vessels are obliged to use AIS, hence radar data need to be included to ensure safety and security.

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