Supporting Event-Based Geospatial Anomaly Detection with Geovisual Analytics

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Abstract: Collecting multiple geospatial datasets that describe the same real-world events can be useful in monitoring and enforcement situations (e.g., independently tracking where a fishing vessel travelled and where it reported to have fished). While finding the obvious anomalies between such datasets may be a simple task, discovering more subtle inconsistencies can be challenging when the datasets describe many events that cover large geographic and temporal ranges. This paper presents a geovisual analytics approach to this problem domain, automatically extracting potential event anomalies from the data, visualizing these on a map, and providing interactive filtering tools to allow expert analysts to discover and analyze patterns that are of interest. A case study is presented, illustrating the value of the approach for discovering anomalies between commercial fishing vessel movement data and their reported fishing locations. Field trial evaluations confirm the benefits of this geovisual analytics approach for supporting real-world data analyst needs.

1 INTRODUCTION

The analysis of event-based anomalies between multiple geospatial datasets is a challenging task, due to the geotemporal complexity of the data (Dykes and Mountain, 2003; Kraak and de Vlag, 2007; MacEachren and Kraak, 2001). However, such analyses can provide useful insights, helping analysts to identify trends and patterns among the activities upon which the data were collected, as well as identifying potential problems with the data collection, data processing, or even intentionally introduced inaccuracies. While simply visualizing the data in layers on a map may allow for the obvious to become apparent, discovering previously unknown anomalies within the data can be challenging.

Although geospatial datasets may take multiple forms with varying complexity, this research considers geospatial events, independently described by movement and geographical point datasets. These independent datasets represent the actions of the same conceptual entities, but from different perspectives (e.g., the movement of an entity over time, and the location and time at which the entity performed some notable action). When the temporal granularity between the datasets is synchronized, detecting anomalies can be done with a simple distance calculation. However, such synchronization is not guaranteed for independently collected data sets. Thus, uncertainty is introduced into the anomaly detection process, necessitating the need for human-centred analysis to separate the meaningful anomalies from those that are a result of the mismatch between the temporal scales.

Following a geovisual analytics approach, this research combines automatic data processing methods with information visualization and human-computer interaction techniques, with the goal of supporting data exploration, analytic reasoning, information synthesis, and decision-making (Keim et al., 2008), with special consideration given to the geotemporal aspects of the data (Andrienko et al., 2007a). After matching the datasets and calculating the potential for the events being anomalous, these are represented on a map allowing the analyst to examine their relationship with one another. Interactive filtering tools are provided to address information overload issues associated with showing too much data at the same time. These include spatial, temporal, and attribute-based filtering, along with novel anomaly threshold filters that control how the datasets with different temporal granularities are matched to one another. Interactively manipulating these filters to focus on a particular type of anomaly being investigated allows analysts to hide uninteresting features of the data in order to isolate those that are of interest. Individual entities can be inspected in detail, showing their complete movement path and linking them to other anomalies that may have occurred for the same entity.

While many situations exist in which data is being collected from multiple sources that relate to the same conceptual entity, this particular research was motivated by the challenges of comparing where fishing vessels have travelled and their reported fishing locations. Anomaly detection in this domain can be used for detecting data entry errors and instrument failures, as well as for enforcement purposes. Because of the significant differences in temporal granularity (hourly fishing vessel position data and daily fishing location data), automatic methods are difficult to tune in order to find the important anomalies and avoid an overload of false-positives. Manual analysis often consists of detailed visual inspection and comparison, requiring significant cognitive effort and focus. The geovisual analytics approach described in this paper automates the menial aspects of anomaly detection, allowing the analysts to consider, examine, and explore among a much larger number of potential anomalies than with their existing methods. This is illustrated with a case study, and supported with the results of field trial evaluations with expert data analysts.

2 RELATED WORK

While much of the research on geovisualization and geovisual analytics focuses on exploration within a single geospatial dataset, some have studied methods for handling multiple related datasets. In addition to the traditional approach of layering multiple datasets on the same map, more advanced approaches have been explored. For example, it is possible to transform and merge multiple geospatial datasets together into a common viewing framework (Treinish, 2000). Alternately, multiple coordinated views of the different datasets may be provided (Johansson and Jern, 2007; Mandiak et al., 2005), such that manipulations in one representation (e.g., panning and zooming) affect the configuration of the others. In cases where the multiple datasets contain many different attributes, parallel coordinate plots have been used to filter the data and choose which aspects to show on the map (Lundblad et al., 2009).

When the geospatial data represents the movement of entities through space and time, new complexities are introduced in the representation and analysis of such movement data (Kraak and de Vlag, 2007; Andrienko et al., 2012). While flow lines can support the interpretation of the movement paths, simultaneously representing the data from many entities often results in a visually complex display that is difficult to decode (Enguehard et al., 2013). Some alternatives to addressing this problem include using animation (Andrienko et al., 2000), taking advantage of the third spatial dimension with space-time cubes (Kapler and Wright, 2005; Kraak, 2003), performing automatic machine learning on the data to extract and represent the high-level features (Andrienko et al., 2007b), and providing complex methods for interactively filtering the data to highlight the interesting low-level features (Enguehard et al., 2013).

A further challenge with using movement data is extracting events based on the motion and contextual characteristics of an entity. Andrienko et al. (2011) proposed a general approach to extract noteworthy events from movement data, treating these as independent objects. They suggest a conceptual model in which movement is considered in relation to events of diverse types and extents in space and time. With this model, the relationships between movement events and elements of the spatial and temporal contexts in which those events are occurring can be visually represented and analyzed.

While the aforementioned works have sought to find similarities between elements within the geospatial data, either automatically (Andrienko et al., 2011) or based on interactive exploration (Enguehard et al., 2013), few have approached the problem of finding differences, discrepancies, or anomalies. The LAHVA system (Maciejewski et al., 2007) was designed to extract events from human emergency room data and veterinary hospital data, providing a visual interface to allow analysts to detect similarities and differences in order to identify disease outbreaks before they become epidemics. GTdiff (Hoeber et al., 2011) took a small multiples approach to visually representing the changes in a geospatial dataset, organizing a series of difference graphs in an inverted pyramid structure to allow analysts to explore where and when the data have changed. While these approaches work well when the datasets are temporally synchronized to one another, they do not address the situation where there may be a mismatch in the granularity at which the data was collected.

3 PROPOSED APPROACH

The focus of this research is to explore methods for automatically extracting anomalies from independently collected movement and geographical point data that represent the activities of the same conceptual entities, and to visually represent this information within an interactive interface that supports exploration and analytical reasoning about the anomalies and their underlying sources. In order to realize this goal, four critical elements are necessary: (1) event extraction, (2) geospatial anomaly detection and thresholding, (3) anomaly representation, and (4) interactive filtering and exploration. Here, we outline the key elements of each of these aspects of our research, along with a brief description of the implementation details.

3.1 Event Extraction

The event extraction process in this work is based on the knowledge that the geospatial point dataset has captured the existence of the events of interest. Using common identifier fields between the two datasets supports the matching of these events to their associated entities in the movement dataset. The complicating factor is the potential mismatch between the temporal granularity of the datasets.

If the movement data is at a higher level of granularity than the geospatial point data, then a pair of movement data points will be mapped to a single event data point, representing where the entity was before and after the event occurred. Alternately, if the movement data is at a lower level of granularity than the geospatial point data, then a series of movement data points will be mapped to the event, representing the path of the entity during the temporal range of the event. In either case, there is a degree of uncertainty in the matching of the data, which must be addressed when seeking anomalies.

3.2 Geospatial Anomaly Detection and Thresholding

Once the movement data and geospatial point data are matched together in the context of the events, the task then is to detect whether any geospatial anomalies exist within the events. The approach taken in this work is to consider both the geographic distances between the event and the entity location, and the amount of time (i.e., the number of movement data points) the entity spent within an acceptable distance threshold. For example, in the case where there are multiple movement data points captured at hourly intervals and related to a single event that occurred sometime during a six hour period, the event may be considered normal if the entity was within a distance of 1 km for three or more hours, and an anomaly otherwise.

Figure 1 illustrates three possibilities within this scenario. Here, the movement data is shown with arrows indicating the movement direction, and the location of the event is shown as a point in space with a circle indicating the threshold distance that is considered acceptable. In the first case (Figure 1(a)), the entity was not within an acceptable distance from the event at any time. In the second case (Figure 1(b)), the entity was within an acceptable distance from the event, but only long enough for two data points to be captured. In the third case (Figure 1(c)), the entity was near the event location for four continuous hours. As a result, in this example, we may consider the first and second cases anomalies, and the third normal.

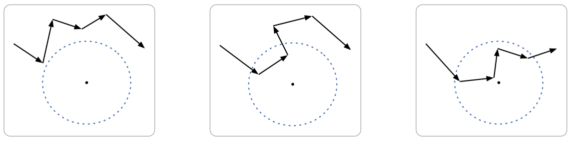

(a) (b) (c)

Figure 1: Examples of potential anomalies between movement paths and event locations.

A unique feature of this approach is the use of two parameters for determining whether a specific event is considered an anomaly, one based on space and the other on time. Choosing appropriate threshold settings for these parameters cannot be done automatically, since they require domain-specific knowledge regarding the actual activities of the entities. As a result, interactive support is provided to allow analysts to manipulate these threshold parameters in order to filter the set of potential anomalies to show those that exhibit abnormal behaviour. Simple slider controls are employed for this purpose, supporting independent adjustment of the minimum distance from the reported event and the amount of time the entity is expected to have been within this distance radius.

3.3 Anomaly Representation

Representing anomalies that have been detected in the context of the movement of entities requires visual encoding of multiple aspects of the data. These include representing the movement paths of the entities, the locations of the events, and the positional discrepancies between the two. Anomaly visualization should allow analysts to visually group data corresponding to the events and the movement paths easily and quickly, while at the same time, not overwhelm them with a visual representation that is difficult to interpret.

Since in the context of this work the positional discrepancies between the datasets are the essence of the anomalies, it is important to illustrate these clearly. Taking advantage of the Gestalt Principle of Connectedness (Koffka, 1935; Palmer and Rock, 1994), each anomaly is represented by the graphical connection of a line between the event location and the nearest position on the movement path within the associated timeframe. Representing anomalies in this way is a powerful mechanism for expressing the relationships between the data, supporting pre-attentive processing (Ware, 2004). An added benefit of this approach is that the severity of the anomalies will automatically be visually encoded, with more extreme anomalies carrying more visual weight in the display due to the length of the connecting lines.

It is also important to represent the paths of the entities from the movement dataset in a way that can readily be perceived and interpreted as a movement path that is distinct from the connection to the event. For this, flow lines are used, with chevrons representing the locations of the movement data points along with the direction to the next data point in the series. Since the chevrons can add visual complexity to the movement path when there are a large number to display, these can be interactively hidden or shown.

Representing such data on a geographical map in a way that can readily be perceived and correctly interpreted is challenging (MacEachren and Kraak, 2001). In particular, it is important to make careful choices of the colours for the movement data flow lines and the anomaly lines used to connect these to the event locations. Knowing the ambient colours used to represent the geographical features on the map can allow for the selection of a set of colours that are perceptually distinct from the base map. For example, it is common to represent oceans and land on a map using shades of blue and green, and other features using black or grey. Following the Opponent Process Theory of Colour (Hering, 1964), this leaves yellow, red, and white as perceptually distinct colours for representing aspects of the data.

An example showing a set of significant anomalies within an oceanic dataset is provided in Figure 2. Here, one can readily identify the movement paths of the entities and the severity of the anomalies. In addition the pattern of the anomalous behaviour can also be observed and interpreted. While there remains some overlap and clutter in this display, the selection and highlighting features described in the following section support an interactive disambiguation of the anomalies.

It is also important to consider how to deal with and represent situations where there are missing data points in the movement dataset. This is a concern, since it is common for movement datasets to be collected remotely, using a regular time interval for logging the data. When there are communication problems, data points may not be properly saved in the dataset, leading to missing data. For these situations,

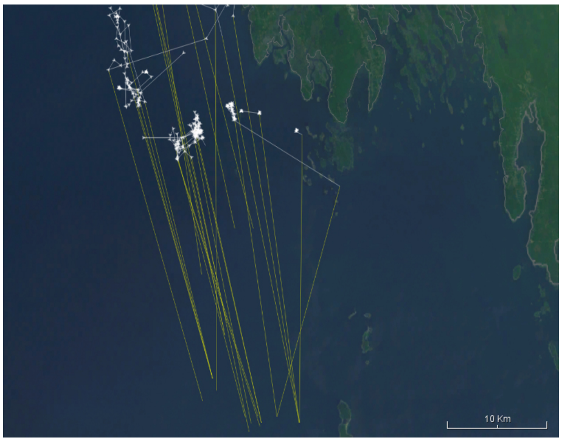


Figure 2: Anomalies are represented by the yellow line connecting where an event was reported and the white movement path of the entity.

in order to maintain a consistent representation of the movement activity, the missing data is interpolated on a straight line between the known data points. Since an anomaly may be detected as a result of this missing data and the interpolation method for filling in the gaps, it is important to visually convey this interpolation back to the analysts. This is done by replacing the chevrons that represent the movement data points with empty circles. However, because in some cases a few missing data points may not have much of an affect on the anomaly detection, an option is provided to allow the analyst to determine how many missing data points are necessary in order for these to be highlighted as distinct from the regular movement path representation.

Since it can be difficult to systematically inspect each anomaly when they are represented only on a map, a secondary representation is also provided. Event anomalies are grouped by their entity identifier, and represented in a tree structure to facilitate interactive selection. Each entity for which at least one anomaly was detected is included as a node at the top-level of the tree. Along with the entity identifier, information about the number of anomalous events and the total number of events are provided. Individual events for a given entity are included as children of the entity node, showing the timestamp and domain-specific data about the event. A checkbox beside each node in this tree structure allows for the visibility of the anomalies to be toggled within the map display. This tree structure and map operates as coordinated views, dynamically updating what is shown in each based on interactive filtering and focusing. This is illustrated in a screenshot of the entire interface display, provided in Figure 3.

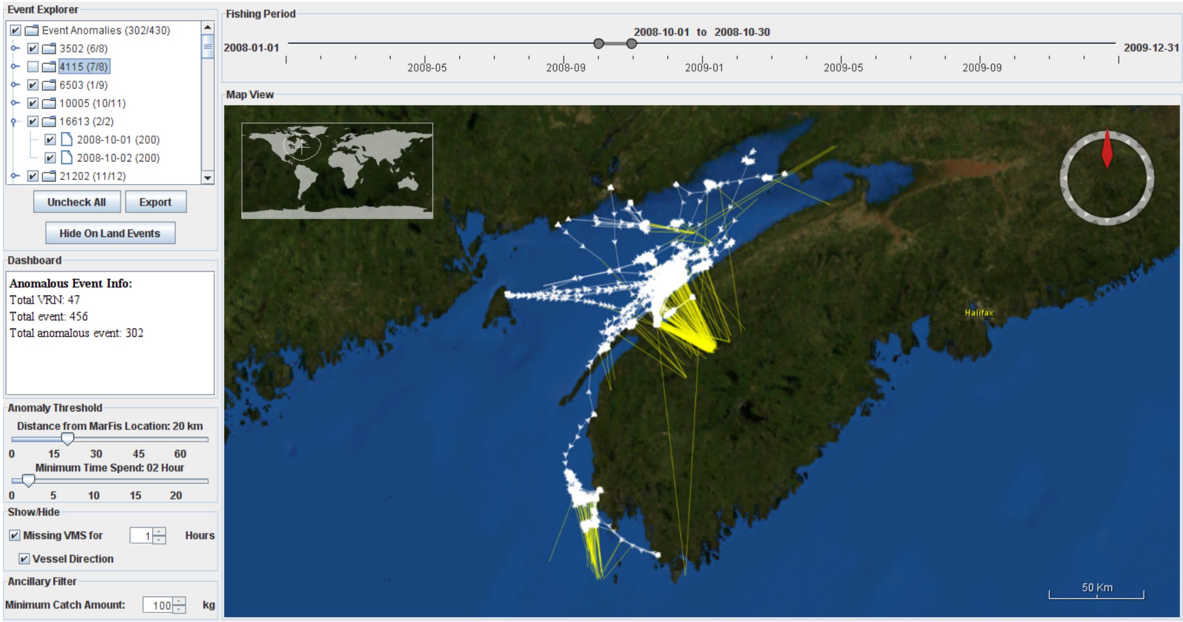


Figure 3: The interface for event-based geospatial anomaly detection and exploration includes a temporal filter (top-right), map view of the movement paths and anomalies (bottom-right), tree representation of the entities and anomalies (top-left), and interactive filters (bottom-left).

3.4 Interactive Filtering and Exploration

Interactive filtering is provided by four analyst-controlled parameters: temporal extent, spatial extent, anomaly thresholding, and ancillary data filtering. By filtering out uninteresting or obvious anomalies, analysts are able to focus their attention on those that are of particular interest. Any modification of these parameters results in an interactive update of the anomalies shown in all views of the system, allowing the analysts to readily see the results of their actions.

The temporal and spatial filtering features operate using commonplace interface controls and interaction mechanisms. A timeline is provided showing the temporal range of the datasets. A temporal window control allows analysts to modify the upper and lower bounds of the window, as well as pan the window over the temporal range. The spatial filtering operates within the geographic representation, allowing analysts to zoom to the desired spatial scale and pan to regions of interest.

As previously noted, the anomaly threshold controls can be used to filter the data to only show those that match the spatial and temporal threshold parameters. Two slider controls allow analysts to set the acceptable distance between the event location and the associated movement data points, and the amount of time the entity must have remained within this distance. All events that exceed these parameters are considered anomalies and are displayed with the system; all others (e.g., normal behaviour) are hidden.

In many cases, when an event occurs, there is additional data that is collected in the context of this event. For example, in the motivating case for this research, when a fishing event occurs, data on the catch amount is logged. In the context of detecting anomalies, we consider this ancillary data, and provide a mechanism for the analysts to filter what is shown based on this data. Another type of ancillary filter can be used to hide data that is clearly not possible. For the fisheries case, this will remove anomalies where the reported fishing location is on land.

These interactive features for filtering the data can be used to address a common concern with geovisualizaiton and geovisual analytics: the visual clutter that arises when many data elements are displayed in close spatial proximity (Jänicke et al., 2012). Temporal, spatial, anomaly threshold, and ancillary data filtering all enable the analyst to interactively control how much data is shown. An example of this is shown in Figure 4, where a large number of anomalies is reduced to a manageable number through interactive filtering.

The highlighting of one or more anomalous events is enabled by clicking on the anomalies within either the map or tree views, supporting an interactive inspection of the data. Doing so changes the colour encoding of the movement path for the anomaly from

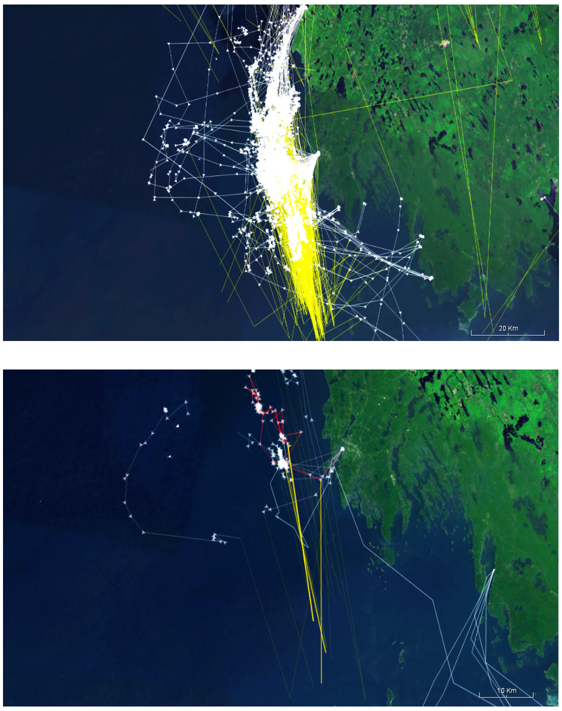


Figure 4: Showing all potential anomalies within the datasets can result in significant visual clutter (top). Interactive filtering and a narrowing definition of what it means to be an anomaly can allow the analyst to focus on a small number of anomalies to examine in detail (bottom).

white to red, both for the selected anomalous event, as well as for any other anomalies for this same entity. Additional contextual information of the movement path of the highlighted entity within the selected temporal range is added to the display as white lines without directional markers, providing contextual information of where the entities travelled before, between, and after the anomalous events. In addition, the visual intensity of the anomalies are provided at three different levels: the highlighted event is shown at a high level of intensity; other anomalies for this entity are shown at the normal level of intensity; and all remaining non-selected anomalies are shown at a low level of intensity. This allows the analysts to readily see what was selected, along with other contextual information about the entity, while fading the remaining data to the background (see Figure 5).

4 CASE STUDY

In order to illustrate the features of the proposed approach for event-based geospatial anomaly detection, a case study is presented in the context of commercial fishing datasets. The datasets were collected for the

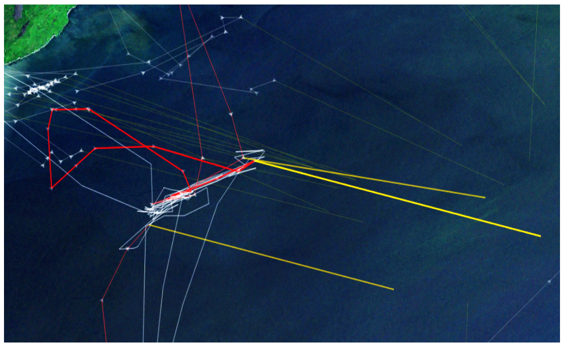


Figure 5: Highlighting an anomaly changes the colour encoding of the path of the entity to red and increases the brightness of the yellow link to the event location. Other anomalies for this same entity remain at the normal visual intensity, and all others are faded to allow the analyst to focus on what was selected.

inshore scallop fisheries in Atlantic Canada over the two year period of Jan 1, 2008 to Dec 31, 2009. One of the stipulations for receiving a commercial fishing license in Canada is that each fishing vessel must be equipped with a Vessel Monitoring System (VMS), which automatically and independently records the GPS location of the vessel on an hourly basis. Upon returning to the port after a multi-day fishing voyage, the vessel must report where it fished each day, as well as the amount of fish caught in each location. This data is logged in the MarFis database system, along with details regarding the fishing vessel identifier and license. The data analysis goal in this case study is to explore and understand the spatial discrepancies between these two datasets that are meant to describe the same conceptual entities (fishing vessels) and their noteworthy events (fishing activities).

These particular datasets contain a substantial amount of data that must be analyzed to identify anomalies. From the MarFis data, 209 fishing vessels preformed a total of 18,030 fishing events during the two-year period, representing an average of 43.1 fishing events per vessel per year. Within the VMS data, 1,967,341 data points were collected for these fishing vessels, representing an average of approximately 196 days at sea per vessel per year. This discrepancy between the average days of fishing scallop and the average days at sea is a result of the limits on the scallop fishing season and the common practice of fishing vessels obtaining licenses to fish multiple species throughout the year. Of note is the temporal mismatch between the two datasets: the VMS data contains hourly fishing vessel locations, while the MarFis data contains daily locations of where they fished. As a result, extracting and analyzing anomalies is not as straightforward as it would first appear.

The current anomaly analysis practice among fisheries experts is to map each dataset independently, and then manually inspect and compare the maps to find anomalies. Clearly, doing this for many vessels over a long period of time and a large geographic range is not feasible. As such, a first analysis step is to identify a small subset of vessels to study in detail. The selection criteria may include choosing specific vessels over a specific time period, specifying vessels based on having been near some point of interest such as a marine protected area, or even performing random sampling for inspection purposes. With the data filtered in this way, the process of tracing the movement of a particular vessel on one map and comparing it to where it reportedly fished on another map is cognitively complex and requires a great detail of focus and attention. Even using GIS approaches that support multiple views and interactive layers does not alleviate the cognitive task of having to manually link the data. Because of the effort involved, this type of analysis is generally only done when there is already a clear indication of the existence of noteworthy anomalies within the data for a particular subset of vessels. This means that this approach is seldom used to discover anomalies, but is instead used to verify those that are already suspected or known.

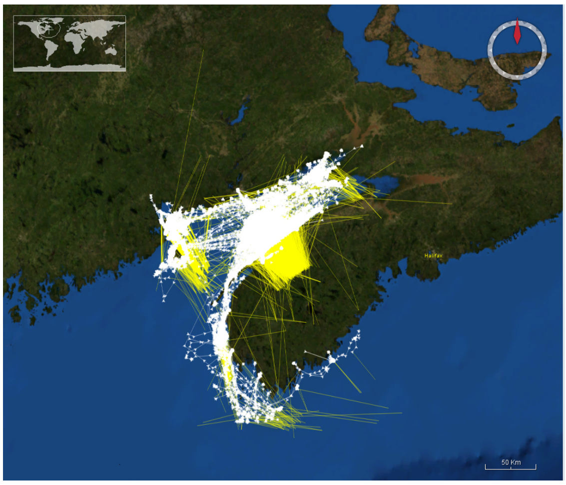
Using this geovisual analytics approach for detecting and discovering new anomalies in the data, a good starting point is to view the entirety of the data with a generous definition of what constitutes an anomaly. For example, in the context of fishing for scallop, normal fishing events might be defined as those for which the vessel was within 40 km of the reported location for more than 5 hours. The specific settings for such an anomaly threshold filter would be based on the analyst's experience with the fishing practice (e.g., how long fishing sessions normally last, as well as how far they normally travel in this time) and the expected accuracy within the data. With this particular dataset, such a first-pass filter eliminates 12,789 normal fishing events, leaving 5,241 for further exploration and filtering. While showing these within the system results in a significant amount of visual clutter (see Figure 6(a)), it does provide a high-level overview of the extent and pattern of anomalies within the data. Even from this cursory analysis of the data, it is clear that there are a significant number of cases for which the fishing location was reported on land. While this fact may have been discovered simply by mapping all of the fishing locations within the MarFis data, the extent of the problem may not have been clear due to the common practice of only inspecting a small number of vessels during a limited period of time.

To further explore among the anomalies, the analyst may choose to focus on data for a particular period of time, and remove those anomalies that have the fishing location reported on land. Figure 6(b) shows 43 anomalies detected among a total of 466 fishing events in the month of September 2008. Further reduction of the visual clutter is achieved by hiding the directional markers on the fishing vessel movement data, since at this level of detail the vessel direction is not contributing to insight into the data.

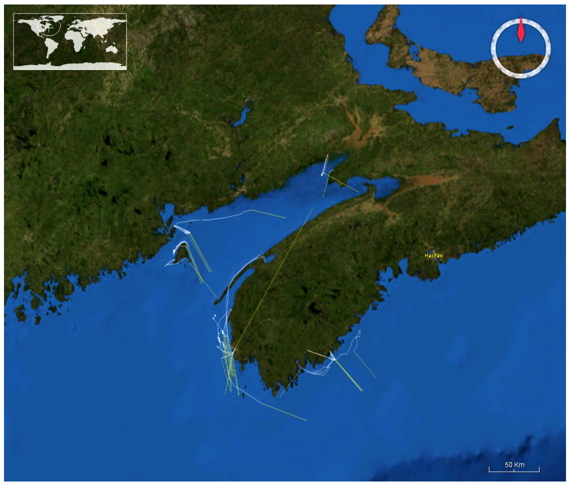
Based on the analyst's knowledge of the fishing practice within this region, the anomaly threshold could be configured to require the vessel to be closer to the reported fishing location (e.g., within 25 km), but for less time (e.g., at least 2 hours). The analyst may also wish to view only those fishing events for which a large catch amount was reported (e.g., 300 kg or more). Doing so reduces the total number of fishing events to 328, of which 34 are detected as anomalies. These are illustrated in Figure 6(c), from which three separate geographical regions can be readily identified in which anomalies are present: the northern bay region, the central bay region and the southern region.

Noting the large number of anomalies in the southern region, the analyst may use the pan and zoom features of the map to focus on the anomalies in this region. For this detailed analysis, the analyst may also choose to enable the vessel direction indicators. Within this spatial region, a total of 25 anomalies remain for further exploration and examination (see Figure 6(d)). Viewing these anomalies, the analyst can readily identify clusters of where the fishing vessels were spending their time, yet all of these vessels are reporting their fishing locations for these days significantly further south.

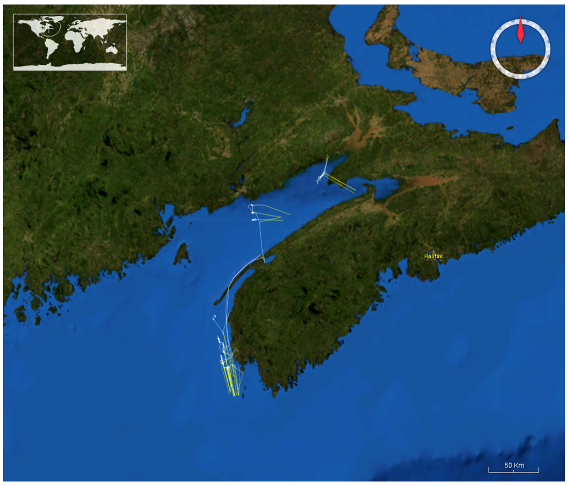
In order to support the analyst in understanding the potential causes of these anomalies, individual vessels may be selected for detailed inspection and evaluation. Upon making such selections, the anomalies from the other vessels in the region are dimmed, the selected anomalies and their vessel paths are highlighted, and contextual information regarding the paths of the vessels before and after the anomalous event are included in the display. Further insight into potential problems can also be provided by turning on the highlighting of missing VMS data points. From this view of the anomalies (see Figure 6(e)), the specific activities of the highlighted vessels can then be inferred based on what is being shown. For example, the vessel on the right indicated fishing at the exact same location on four separate days, but did not come within 25 km of this location. In addition, there is one particular period of 11 hours in which the vessel's VMS system was not responding. While this may be an indication of equipment failure, it could



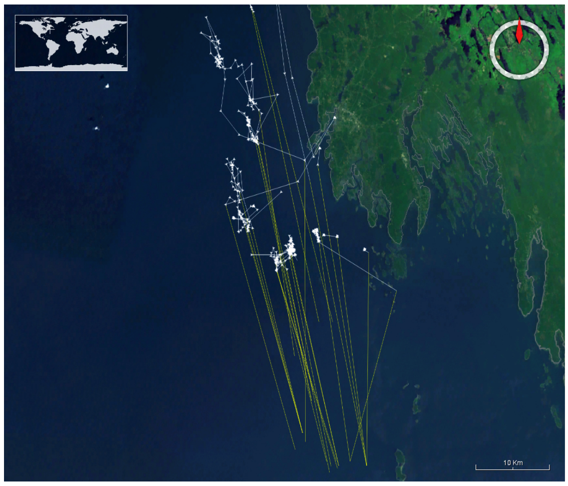
(a) All anomalies within a two-year period.



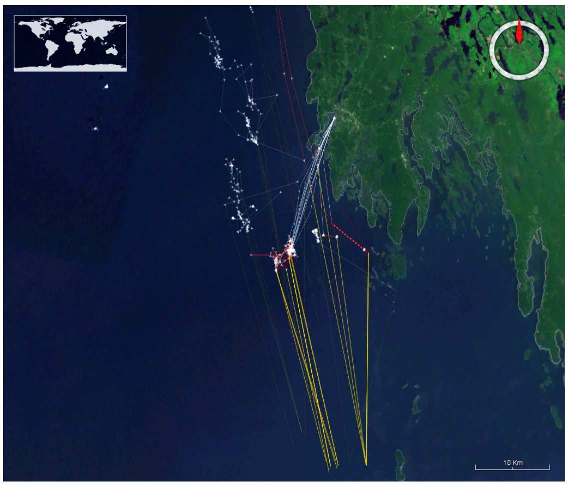
(b) Filter to one month of data.



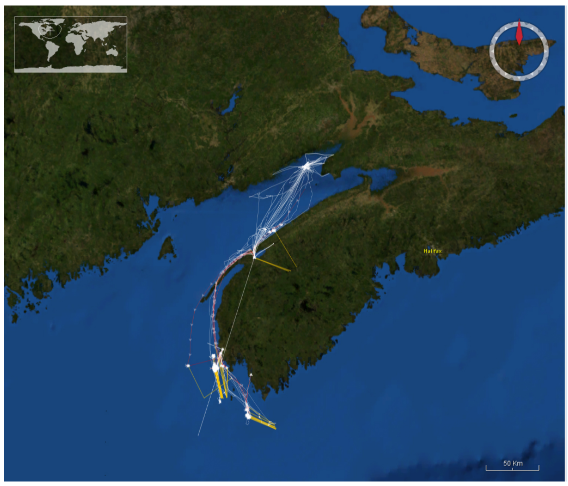
(c) Defining anomalies more strictly.



(d) Zooming into a spatial region.



(e) Highlighting specific vessels.



(f) Zooming out to provide context to the anomalies.

Figure 6: This series of screenshots of the map interface illustrate the interactive filtering, exploration, and highlighting of anomalies within a fisheries dataset. Temporal filtering, anomaly thresholding, and spatial zooming allow an analyst to explore the patterns of anomalies, and discover particular vessels that require further investigation.

also have been a result of intentional equipment sabotage in order to disguise illegal activities. By contrast, the vessel on the left made many trips back and forth between a nearby port and a fishing region just 15-20 km from port, but reported the fishing location at least double that distance. However, in this particular case, the vessel moved around the fishing region in a pattern that is indicative of fishing activity, but took efforts to report locations that were distant from this location and that slightly varied from one another. In both of these cases, using the proposed approach gives the analyst some insight into the activities surrounding the anomalies, providing evidence to support supplemental investigation of these particular vessels.

Further insight and context regarding these vessels and their anomalous fishing events can be obtained by zooming out to explore where else the vessels have been travelling, broadening the temporal range in which the data is shown, and including those anomalies that are on land. In such a case, the analyst may also wish to completely hide all other anomalous events in order to avoid misinterpretation and visual clutter. Figure 6(f) shows the movement paths and anomalies for these two vessels over the entire scallop fishery region and a six-month period. From this view, it is clear that data is normally reported properly when fishing within the bay region (with the exception of a few data entry errors that put the fishing location over land), but when the vessels travel to the southern peninsula, they consistently misreport their fishing locations. From a fisheries management and enforcement perspective, this may be an indication that there is a need for more monitoring in the southern region of the fishery.

This case study illustrated how the visual and interactive features of the system support not only an exploration of the anomalies within the data, but also analytical reasoning about the underlying behaviour that has caused the anomalies. The system is highly interactive, allowing analysts to easily focus on a geographic and temporal range of interest, as well as set the parameters for what constitutes an anomaly. Specific anomalies can be compared to one another within the geographic context, for the same vessel as well as across multiple different vessels. Patterns of anomalies can be extracted, and using their existing knowledge about the domain in question, analysts can readily interpret these (e.g., systematic data quality problems, intentional misrepresentations, potentially illegal activities). In comparison to the existing practice of analyzing this fisheries data, the use of this geovisual analytics approach supports more than just verification of what is already known, but also discovery and analysis of what was previously unknown.

5 FIELD TRIALS

Further validation of the proposed approach was obtained via a set of field trials conducted with real world data analysts working in the fisheries domain. Rather than studying each of the novel elements of this work in isolation, these field trials take a holistic approach to the evaluation, focusing on the support the software provides to the practice of event-based geospatial anomaly detection and exploration. The use of field trials for evaluating systems such as this are beneficial when the data analysis activities are complex, there are a limited number of experts available, and there is no reasonable system against which to make a comparison. They provide real-world evidence of the value the approach provides for supporting the actual activities of the target users (Lam et al., 2012; Plaisant, 2004).

The target participants for these field trails were professional fisheries data analysts working at Fisheries and Oceans Canada. Invitations were sent to all the potential analysts who had prior familiar with the analysis of VMS and MarFis data, and the scallop fisheries for which this data was collected. Five participants voluntarily participated, of which four (Participants A-D) had 4-6 years of experience with analyzing this data, and reported high degrees of prior familiarity with visualizing data with various software packages. The fifth (Participant E) had less experience with analyzing the data (1-2 years) and reported moderate familiarity with the visualization methods the others used.

Each participant was given a training session on the use of the complete range of features of the software. The participants were then invited to use the software themselves in the exploration and analysis of anomalies within the same two-year dataset described in the case study. This use of the software was driven by the participants' interests and expertise in the fisheries domain, and was entirely open-ended and self-directed. When necessary, the investigator helped the participants to operate the software, allowing them to perform their tasks at a level beyond the novice level. Once the participants felt they had sufficiently evaluated the anomalies within the data, a post-study questionnaire was administered using a survey instrument adapted from the Technology Acceptance Model (Davis, 1989). An interview was also conducted, focusing on the participants' qualitative impressions of the software and the types of anomalies they were able to discover during the course of the study.

While using the software for their self-directed data analysis activities, we observed the participants following the same pattern of filtering and exploring among the data. They started with setting the temporal range and configuring the anomaly threshold filter, and then zoomed to a geographical region of interest. After observing the anomalies present in this region, they each undertook further filter refinement steps, including setting the ancillary data filter, re-focusing the spatial filter, adjusting the temporal filter, and refining the anomaly threshold settings. Doing so brought the number of anomalies displayed on the map down to a manageable number, allowing the participants to highlight particular vessels and evaluate the details of the anomalies. In using the software, all of the participants were able to find and evaluate specific anomalies, conducting detailed investigations of their activities before, during, and after the event in question to try to make sense of what was happening.

While the participants were already highly experienced in analyzing these data, most expressed their surprise by the large number of anomalies present. This finding highlights the difficulty they currently experience in performing anomaly analysis between these two datasets. While they have tools to map the two datasets independently, matching the fishing events to the fishing vessel movement paths, and then studying the anomalies in detail, requires a significant amount of cognitive effort. Participant D noted that "without tools like this... it is very difficult for anyone from enforcement to deal with this kind of problem." This participant further noted that doing this type of analysis with their current software systems "is too tedious."

The post-study questionnaire administered after the participants finished using the software focused on the their perceptions of usefulness and ease of use of various aspects of the software. For each feature, six related questions were asked for each of these measures, with answers provided on a five-point Likert scale. Although each participant had a different analysis goal while using the software, we observed that they made full use of the features of the software to support their analysis tasks. As such, we report here the aggregated responses for each specific feature of the software.

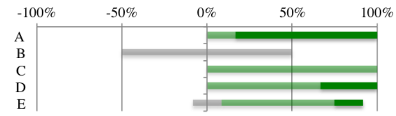
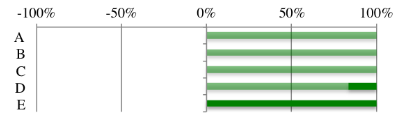
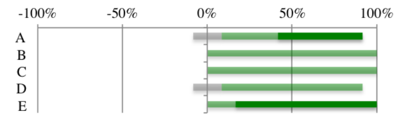
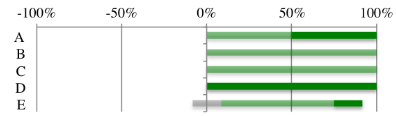
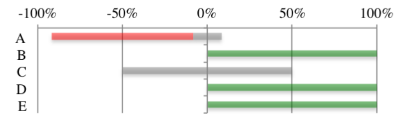
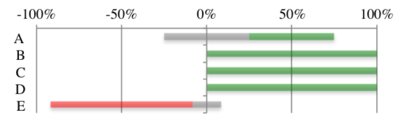
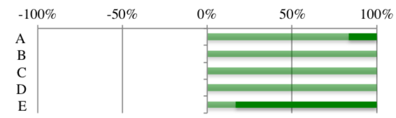
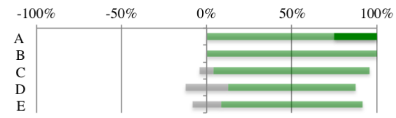
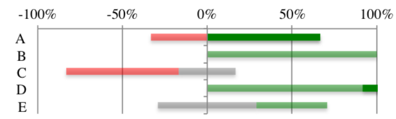
The perceived usefulness and ease of use of each of the key features of the software are reported separately for each participant (A - E) in Table 1. Note that since the anomaly representation feature is something that is observed but not manipulated, no data was collected regarding its ease of use. While most participants had a positive view of the usefulness of the features of the system, one was neutral about the anomaly representations and another was negative about the ancillary data filters. Given the open-ended nature of the analysis activities, these negative responses may be attributed to the feature not being useful for the specific type of analysis the participant was undertaking. In terms of ease of use, while the responses were generally positive, some participants reported negatively regarding the spatial and temporal filters and the anomaly highlighting. As prototype software, some of this difficulty with using the system may be attributed to its novelty and lack of sophistication in comparison to commercial-grade software.

The analysis of the interview responses revealed a number of common themes. All of the participants commented positively on the method for visually conveying the existence of an anomaly using a line connecting the event location and the vessel movement path, and the method for visually highlighting selected anomalies. They appreciated the value of these methods for not only identifying anomalies, but also for representing the degree of the spatial discrepancy in the data. Participant C noted that "in terms of being able to quickly visualize the differences in the data, and the magnitude of discrepancies, this is huge." Participant B echoed this sentiment, stating that "it's an eye-opener for me. I didn't realize that there are some cases where there is such a discrepancy." Participant D noted the value of this approach for identifying which vessels to investigate in further detail: "I am not concerned [about the minor anomalies]. But if the degree is big, then we will have major concern about that."

In terms of supporting the specific anomaly analysis activities, and in comparison to their existing practice for this type of data analysis, all of the participants commented positively on the value of the approach. They indicated that with existing tools at their disposal, their only option is to inspect the data for potential anomalies on a case-by-case basis. Using this software, they identified the ability to view the anomalies over a broad temporal and geographical scale as a significant improvement. Participant D highlighted these differences by stating that "this kind of whole picture is very different than how I look at the data right now. [This new approach] is definitely useful." Participant C noted that using this software "is huge step up in terms of productivity and efficiency compare to what we are currently do, which is basically... running three separate programs."

Some participants highlighted a few basic usability difficulties they had with using the software, and noted additional features that could further enhance the usefulness of the approach (e.g., data export features, the ability to layer additional data on the map, additional filtering mechanisms). However, all of the participants were enthusiastic about the possibility of

Table 1: Aggregated responses regarding percieved usefulness and perceived ease of use for each participant and each feature of the software. Agreement is represented to the right, in light green for agreement and dark green for strong agreement; neutral is in the middle in grey; disagreement is to the left in red, noting that there were no responses that were of strong disagreement.

Feature	Perceived Usefulness	Perceived Ease of Use
Anomaly Representation		
Anomaly Threshold Filters		
Spatial and Temporal Filters		
Ancillary Data Filters		
Anomaly Highlighting		

being able to have access to this software after the field trials were complete. Participant A noted that "if I can have this software package, I would be a happy [person]." Participant D said "its very useful and something that is much needed in our current environment... it would be used almost as a daily tool for me."

6 CONCLUSION AND FUTURE WORK

This paper described the geovisual analytics methods we employed for analyzing geospatial anomalies between movement and event datasets representing the same conceptual entities, but collected independently and at different temporal granularities. A case study for using this approach in the context of fisheries data analysis was presented, along with the findings from field trials conducted with expert fisheries analysts. This research illustrates the great potential for geovisual analytics to support the identification, exploration, and analytical reasoning about event-based geospatial anomalies.

While this research was motivated and conducted in the context of fisheries data analysis, the methods developed generalize to other data analysis domains where there is a need to match and analyze the anomalies between independently collected movement and event datasets for common conceptual entities in off-line or real-time. For example, the movement paths measured from mobile phones and the locations where people use their credit cards at point-of-sale machines can be analyzed to identify potentially fraudulent charges, or tracking the movement of taxis and the reported locations for pick-ups and drop-offs can be used to detect the potential misreporting fares.

Future work includes the development and evaluation of alternate approaches for identifying anomalies between the movement and event location data, the addition of a graph within the timeline to illustrate when the anomalies are occurring, and the implementation of edge bundling approaches on the anomaly representation lines to reduce the visual clutter. Additional features to support the analytical reasoning about the anomalies are also being investigated, such as adding annotations, logging analysis sessions, saving anomaly threshold configurations, and linking the data to other external resources.

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