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Maritime Group Motion Analysis: Representation, Learning, Recognition, and Deviation Detection[§]

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Abstract - ***This paper introduces new concepts and methods in the analysis of group motions over extended periods of time, and applies it to an example from the maritime domain. Group motion analysis includes these challenges: (1) represent complex motion patterns of multiple entities as they execute group maneuvers and behavior patterns; (2) learn these group motion patterns in a qualitative fashion, invariant to the number of entities participating; (3) recognize such learned maneuvers and behaviors as they unfold in future group tracking data; and (4) detect in real-time deviations of an entity from a recognized group maneuver or behavior, as such motion anomalies may indicate a vessel emerging from a group. The approach adopts a linear field theory to represent the relative motions of objects, in combination with learning & recognition methods that self-organize three evolving field parameters into 3D clusters that represent maneuver categories, and categories sequences that represent behaviors.***

Keywords: Group tracks, motion analysis, behavior pattern

1 Introduction

Motion activity analysis of single and multiple entities involves the exploitation of tracks, both fragmented and extended, derived from numerous detections over time of extended objects. Utilizing sensors of various modalities, the problems encountered involve uncertain, missed and latent detections, multiple and varied detections from extended objects, mis-associations of detections across multiple objects, and mis-associations of object detections across multiple sensors. The tools to address these challenges are now well developed [1-5]. To analyze object activity over time, it became necessary to build pure, long tracks. Various methods of feature-aided tracking [6,7] became tools that helped disambiguate mis-associations among close objects and crossing tracks.

In order to make progress in activity analysis from the exploitation of object tracks, the maritime domain became a favorite, since vessels tend to be well separated, and their speeds tend to be slow, compared to sensor resolutions and revisit rates. Again, much progress was made and demonstration systems fielded [8-14]. These methods suffice for one or a few well-separated vessels, but do not generalize to the case of groups of many extended vessels (creating clusters of detections) executing maneuvers and complex behaviors. The community turned to investigating "group tracking" methods [15,16], which aim to estimate group boundaries and centroid position over time, robust to missed and multiple detections of individual entities. Sorting out the members of a group from other background entities, all generating sensor returns, is a huge challenge in itself, though motion activity analysis may help provide new insights to solving this association problem.

Yet none of the tools in our tracking toolbox enables us to address groups of varying numbers of entities executing coordinated maneuvers and complex behaviors that may reveal intent. Such motion activity, by its nature, is qualitative. We must introduce new concepts and methods that steer clear of the above limitations in order to both represent group motion activity and analyze it, so that qualitative descriptors can be learned and recognized from real-time sensor data.

1.1 Challenges and Concepts

This paper introduces new concepts and methods in the analysis of group motions over extended periods of time, and applies it to an example from the maritime domain. Group motion analysis includes the following challenges: (1) represent complex motion patterns of multiple entities which evolve over time to execute coordinated maneuvers and behavior patterns; (2) learn these group maneuvers and behaviors in a qualitative fashion, invariant to the number of vessels participating or number of returns detected by the sensor system; (3) recognize such maneuvers and behaviors as they unfold in real-time in future data sets of short tracks (i.e., positions & velocities); and (4) detect deviations of a vessel from a recognized group maneuver or behavior in

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real-time, as such motion anomalies suggest a suspicious situation emerging from a moving group, or an event that disrupts the normal movements of a group.

Our approach uses a locally linear field theory to represent the short-time track of a group of vessels at each moment in time, whereby individual vessel tracklets serve to sample the evolving local velocity field. An extended group of vessel tracklets then determines the instantaneous field coefficients via linear least-squares estimation. This local vector field is then decomposed into basis motion fields and geometric invariants, *rotation (R), expansion (E) and deformation (D),* relative to a moving group centroid. As the group moves as a whole, the relative vessel motions can execute a maneuver or sequence of maneuvers (i.e., a behavior) over time that is realized as a single trajectory through a 3D parameter space of group quantities *{R,E,D}*. Thus, a complex set of extended tracks or fragmented tracklets of many vessels is reduced to a single track of the group centroid plus trajectory through 3D parameter space. Real-time online learning methods are then employed to cluster the triplet values of *{R,E,D}* into self-organized *categories that represent group internal maneuvers. A sequence of maneuver categories represents a group motion behavior that can also be learned as a category pattern.* To learn and recognize both categories and sequences, we make use of neural pattern learning and recognition methods in combination with complex event processors. A maritime example is illustrated using *OceanWatch* data of the 2010 hijacking of a chemical tanker in the Gulf of Aden by Somali pirate vessels.

2 Technical Approach

The approach can be summarized in a few steps, which will be elaborated on and illustrated below. We focus here on a two-dimensional spatial domain, that of surface vessels forming a moving group, executing complex behaviors.

- Vessel motions are taken relative to the group centroid;
- Vessels velocities sample a locally linear vector field;
- The instantaneous linear vector field can be decomposed into a sum of independent characteristic motions patterns: rotation, expansion, and deformation;
- The 3 geometric invariant parameters of rotation (R), expansion (E) and deformation (D) are determined by least-squares fit of the vessel tracklets to a linear model of the vector field;
- Evolving motion patterns lead to time-varying values of the parameters {R,E,D} which trace a trajectory in a 3-dimensional parameter space, i.e., the *RED-space;*
- Similar triples of {R,E,D} are clustered into categories that quantize the *RED*-space, with each motion category representing a characteristic "maneuver;"
- A trajectory through *RED*-space corresponds to a temporal sequence of maneuvers, or a "behavior;"
- Maneuvers and behaviors describe complex relative motion activity among a group of vessels, independent of the number of vessels, their absolute location, and their absolute heading (e.g., relative to North);
- Once learned, group maneuvers can be recognized in future data in both real-time and forensic modes using pattern recognition in the quantized *RED*-space;
- Once learned, group behaviors can be recognized in future data in both real-time and forensic modes using sequence recognition, i.e., evidence accumulation based on the transitions between motion categories over time;
- The complete behavior of a vessel group is described by the behavior of its centroid and its internal activity sequence of behaviors;
- Deviations by one or several vessels from a group maneuver can be detected by a sudden increase in the residual of its state vector relative to the least-squares fit to the instantaneous linear motion field. The quality of input track-level data will therefore affect the ability to detect deviations, by its affect on the residuals.

Recognizing group behaviors and detecting deviations, can be combined with context to reason about possible intent.

2.1 Vector Field Decomposition and Linear Motion Models

By replacing group vessel positions and velocities with a vector field model relative to a moving centroid, we remove dependency of motion analysis on the number of vessels or number of sensor returns from multiple extended objects. The simplest velocity field model relative to a moving centroid is a zero velocity field, implying the group is moving in a rigid formation, and all behavior is described by the track of the group centroid. The fixed spatial pattern of vessels around the centroid may provide additional information as to intent. The simplest velocity field model that can represent motion of vessels internal to the group is a linear vector field. Higher order polynomial vector fields can describe more complex local motion patterns. But the underlying assumption is that the internal motion field is analytic and continuous in space and time.

A linear vector field is often used to describe the local

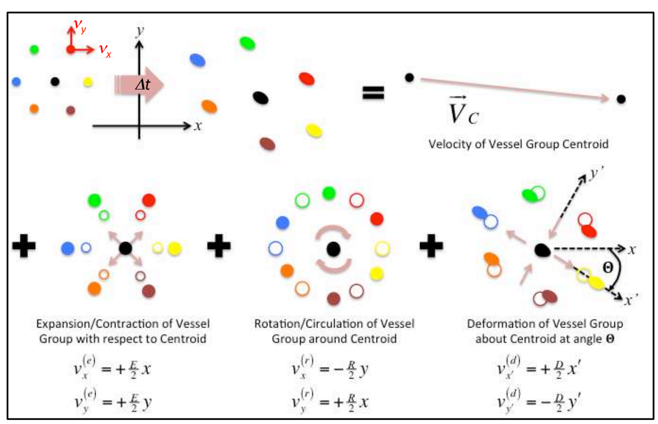

Fig. 1 – A 6-dot motion pattern in 2-D is decomposed as a sum of 3 characteristic linear fields plus its centroid motion.

kinematics of continuous media (fluids, elastics, plastics), and its decomposition into anti-symmetric, and symmetric (both with and without trace) elements of the velocity gradient tensor is attributed to Cauchy and Stokes [17,18]. It has a simple and intuitive graphical interpretation, as shown in Figure 1 for the 2-D motion pattern of 6 colored dots (and their centroid) as they move for a short time. The Cauchy-Stokes decomposition theorem applies to 3-D motion fields as well as 2-D motion fields, resulting in the same 3 geometric invariant parameters *{R,E,D}*. However, there will result two angles (instead of only one here) to describe the orientation of the deformation axis (see Fig.1). These geometric invariants are simply the eigenvalues of the decomposed velocity gradient tensor, and the angles orient the eigenvectors of the traceless symmetric gradient tensor.

For a group detected as N tracklets, the group centroid motion $\boldsymbol{V_C}$ and vessel relative velocity $\boldsymbol{v_i}$ is given by

$$\vec{V}_C = \frac{1}{N}\sum_{i=1}^{N}\vec{V}_i \tag{1a}$$

and

$$\vec{v}_i = \vec{V}_i - \vec{V}_C \tag{1b}$$

The local motion model is a linear velocity field, its spatial derivatives form the elements of the velocity gradient tensor

$$\nabla\vec{v} = \begin{bmatrix} \frac{\partial v_x}{\partial x} & \frac{\partial v_x}{\partial y} \\ \frac{\partial v_y}{\partial x} & \frac{\partial v_y}{\partial y} \end{bmatrix} = \begin{bmatrix} v_{x,x} & v_{x,y} \\ v_{y,x} & v_{y,y} \end{bmatrix} \tag{2}$$

The derivatives are estimated from the *x* and *y* moments of the relative velocities with respect to the centroid (as follows from the least-squares fit to a linear vector field).

We decompose (2) into the sum of three matrixes, the anti-symmetric rotation and the symmetric expansion that are both isotropic, plus the symmetric deformation which is traceless and has its major axis oriented at an angle Θ relative to the *x*-axis (see Fig.1) as determined by its single eigenvalue D. We can write this decomposition most simply in the local reference frame of the deformation eigenvectors

$$\nabla\vec{v} = \tfrac{1}{2}R\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} + \tfrac{1}{2}E\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \tfrac{1}{2}D\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \tag{3}$$

Here, *R* is the group Rotation/Circulation Rate (Curl), *E* is the group Expansion/Contraction Rate (Div), and *D* is the group Deformation Rate (Def). The geometric invariant parameters {*R,E,D*} and orientation angle Θ are obtained from the estimated velocity gradients as follows:

$$R = \left(v_{y,x} - v_{x,y}\right) \tag{4a}$$

$$E = \left(v_{x,x} + v_{y,y}\right) \tag{4b}$$

$$D = \{(v_{x,x} - v_{y,y})^2 + (v_{x,y} + v_{y,x})^2\}^{1/2} \tag{4c}$$

$$\tan\Theta = \frac{D - (v_{x,x} - v_{y,y})}{(v_{x,y} + v_{y,x})} \tag{4d}$$

2.2 Group Behaviors as Parameter-Space Trajectories and Category Sequences

With each (possibly asynchronous) update of sensor reports, tracklets are formed and temporally interpolated back to a common point in time, whereby the estimated positions and velocities are used to determine a linear motion field model according to equations (1-4). This model is described by its three parameters {*R,E,D*} that evolve over time as the vessel group maneuvers. Thus, the group internal motions trace a trajectory through the 3-dimensional *RED*-space. The triplet of values at each update can be used as an input vector to an unsupervised clustering algorithm that quantizes the parameter space in real-time, i.e., it forms categories and adapts category boundaries as the triplet values are formed online. A very effective and simple method for such adaptive online pattern learning,

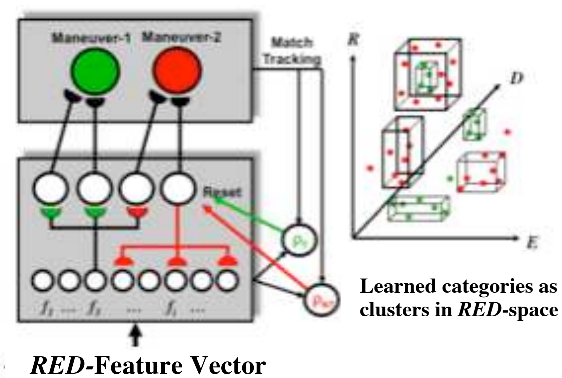

Fig. 2 - Motion *RED*-triplets are quantized by a Fuzzy ARTMAP learning network, forming categories that correspond to hyper-boxes in *RED*-parameter space.

recognition and adaptation of categories, is known as the Fuzzy ARTMAP algorithm [19,20] based on the Adaptive Resonance Theory (ART) of neural pattern learning. We have used Fuzzy ARTMAP extensively for live, real-time, and forensic target and motion pattern learning and detection [6-11]. Figure 2 illustrates the quantization of motion pattern parameters by a Fuzzy ARTMAP learning network, creating categories in the form of hyper-boxes in parameter space. Multiple categories can be learned that become associated with the same class of maneuver, as illustrated in Figure 2, and class names may be assigned by a naval analyst. However, the data clusters/categories themselves form automatically by the learning network.

Figure 3 illustrates the trajectory (red curve linking 81 {*RED*-triplets) traced through motion *RED*-space by a simulated set of 5 maneuvering pirate vessels (described in Section 3) as they head towards an oil tanker transiting the Gulf of Aden. The learning network quantizes the sampled volume of parameter space into only 7 discrete maneuver categories, each containing subsets of the 81 *RED*-triplets.

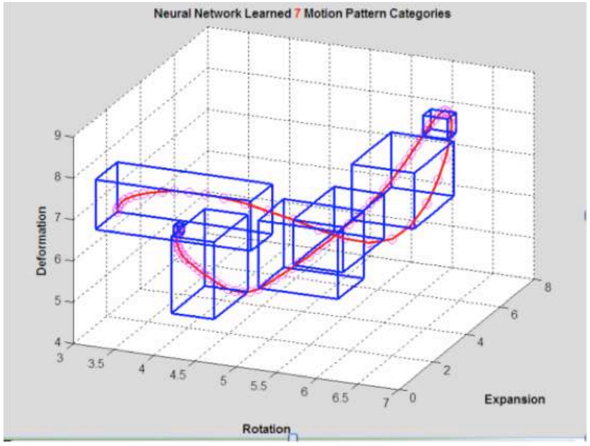

Fig. 3 - A trajectory through motion parameter space is generated by 5 maneuvering vessels. The 81 $\{R,E,D\}$ triplets are quantized into 7 motion pattern categories.

3 Example from OceanWatch Tanker Data + Simulated Pirate Vessels

To illustrate the concepts and methods introduced here, we turn to an example based on the hijacking of the tanker MV Panega while transiting the Gulf of Aden on May 11, 2010 [21]. A fleet of pirate vessels departed from the Somali coast, intercepting the vessel as it took evasive action, and took the crew hostage for 4 months! This event involved two groups of vessels; the Panega itself was sailing as part of a guarded convoy, and the group of pirate vessels that departed from the coast of Somalia. AIS reports were logged from the legitimate maritime traffic in the Gulf of Aden, and that data is available from the unclassified NOAA Ocean Watch database[‡]. We simulated track data for a group of 5 pirate vessels sailing from the coast of Somalia to the Panega's location where it was hijacked. Each of the 5 pirate vessels was assigned a parameterized sinusoidal trajectory, beginning on the Somali coast at the Horn of Africa, and ending at the location of the hijacking event (see the group of colored trajectories at the top of Fig. 6). We will analyze the two vessel groups separately, to illustrate both pirate vessel group behavior learning, and tanker motion anomaly detection.

3.1 Normalcy and Hijacking in the Gulf

Figure 4 illustrates a large number of AIS vessel tracks in the Gulf of Aden, transiting both easterly and westerly along primarily two opposing traffic corridors. Yemen is to the north of the Gulf, the Somai coast is to the south, Djibouti is due west, and the Red Sea to the northwest. Some tracks between ports along the Yemeni and Somali coasts are also apparent.

[‡] We thank Brian Sandberg of CONARCH, LLC, for providing us the AIS data used in this example.

Figure 5 focuses around the time interval of the hijacking, at 15:36 UTC on May 11, 2010. The location of the hijacking event is shown highlighted and zoomed-in, and the AIS reports of the Panega are visible while it is sailed to the tip of the Somali coast where the crew is taken hostage. Of course, the pirate ships weren't transmitting AIS reports, but had there been airborne video surveillance at the time, their small boats might have been detected and tracked [11].

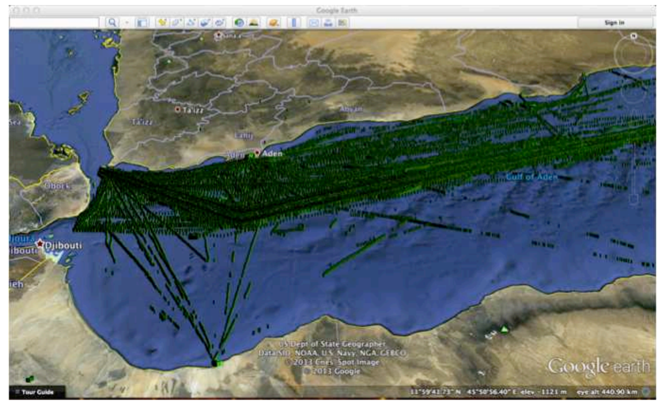

Fig. 4 – Normal vessel traffic in the Gulf of Aden on March 11, 2010 as shown by their AIS reports.

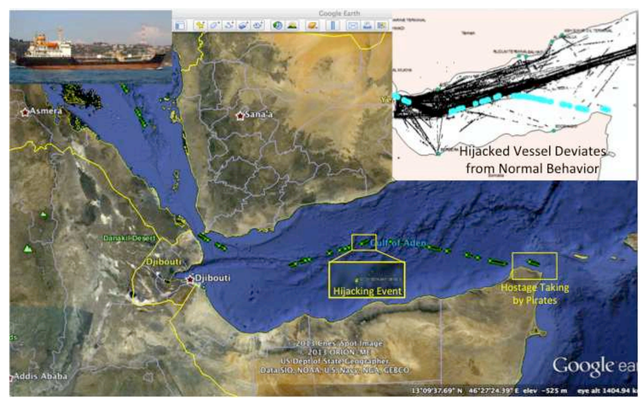

Fig. 5 – The hijacking event occurs when vessel traffic in the Gulf is sparse due to a fog. The Panega sends AIS reports as it is sailed towards the Somali coast.

3.2 Pirate Group Maneuvers & Behavior

Figure 6 (top) illustrates a simulated set of 5 Somali pirate vessel tracks that have departed from the tip of the Horn of Africa and are closing in on the Panega as it transits the Gulf of Aden in a heavy fog. The simulated vessel group tracks are superimposed on the real AIS data set. The red reports (circles) correspond to the westerly lane of vessel traffic. The purple reports (circles) are the vessels heading east including the Panega and its convoy of vessels. Figure 6 (lower left) shows the configuration of the pirate vessels relative to their group centroid (CG) in an evolving lat/long

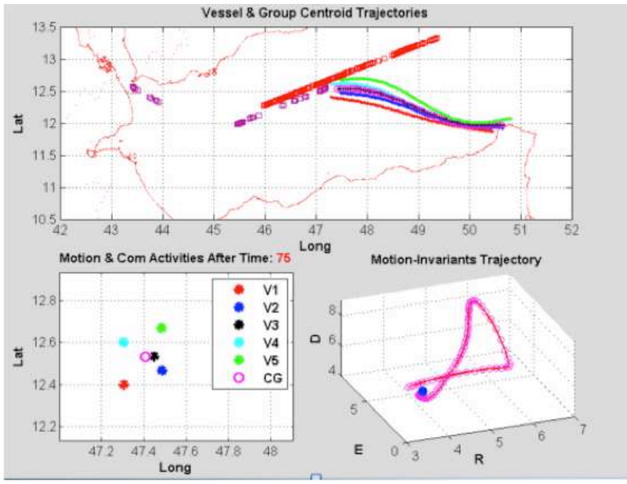

Fig. 6 – Simulated pirate vessel tracks are combined with real AIS data of vessels in the Gulf of Aden at the time of the Panega hijacking. Pirate vessel motions are shown in their centroid frame of reference along with the group trajectory in parametric *RED*-space.

coordinate system. This picture corresponds to frame 75 of 81 frames in a motion sequence. For each frame of the sequence, the motion pattern analysis described in Section 2 has been applied to the simulated group of 5 pirate vessels, and the group internal motion is represented by its trajectory in *RED*-space as shown in Figure 6 (lower right). Thus, while the group centroid motion is a fairly straight track from the Somali coast to the location of the Panega, the *swarming behavior* of the pirate vessels is revealed as the looping trajectory of the group in *RED*-space.

The trajectory in Figure 6 (lower right) is the same one shown in Figure 3, where we found the trajectory could be represented as a sequence of 7 learned maneuver categories. A very similar trajectory, and the same category sequence would likely occur had their been 6 instead of 5 pirate vessels, or only 4, or possibly a varying number of vessels due to noisy object detections and tracks. The point is, that the pirate vessel group exhibits a qualitative behavior that an analyst (or Panega crew member) might characterize as *swarming*.

3.3 Tanker Behavior & Anomaly Detection

We can also analyze the motion of the group of vessels traveling in the vicinity of the Panega, including its guarding convoy. We focus in on those vessels within 20km of the Panega and consider their AIS reports within a 3 hour window around each of the Panega's reports. We also distinguish between those vessels heading west and those heading eastward along with the Panega. Figure 7 (top) shows three temporal frames (time index = 8, 12, 21) that precede the hijacking event. The blue dots indicate the actual lat/long coordinates reported by the Panega's AIS. The open red squares are the interpolated locations of the vessels traveling in the vicinity of the Panega, shown at the corresponding time index. They form a group moving in the easterly lane of vessel traffic. However, the Panega is falling behind its group, and by time index 21 it is rather isolated from the other vessels. (The filled red squares visible in the frame at time index 21 are the AIS reports of a vessel that was heading west.) This progression of vessel motion around the Panega is quite obvious when watching the AIS reports play out as a moving sequence, as was shown at the *Fusion 2015* conference.

Figure 7 (middle) shows the evolution of the *RED*-parameters derived from the AIS reports for the group of vessels traveling in proximity of the Panega, and includes the Panega itself. Rather than plotting this as a trajectory

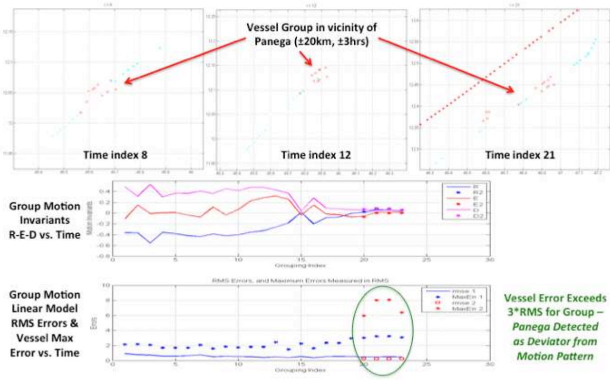

Fig. 7 – Detection of the Panega deviating from its group motion as it tries to evade pirate vessels approaching.

through *RED*-space, we show each of the invariant motion parameters as a function of the time index for the group. The group motion parameters evolve smoothly, though at time index 15 there is a sudden jump due to the lack of AIS reports around that time (as is evident when viewing the AIS movie). The bottom panel of Figure 7 graphs the RMS error associated with the least-squares fit of the AIS track data to the linear velocity field model (blue curve) as well as the maximum error between each AIS derived data point and the estimated motion field model (blue asterisks). We see that the group RMS error remains below 1, while the max data point error starts to grow around time index 19, at which time the maximum vessel error exceeds, by a factor of 3X, the field RMS error. If we remove the vessel with this maximum error, and then re-compute the linear model for the remaining vessels, the RMS error drops to about 1/2 (red squares) and the deviation of that max error vessel from the new linear model exceeds by 6X or 12X the new RMS value. *The vessel producing this very high deviation from the remaining group motion field is, indeed, the Panega. Its motion has become anomalous with respect to the group it had been traveling with.* Having fallen behind its group, once it saw the approaching pirate vessels, it began to take evasive action. This maneuver stood out as different from the rest of the group in its convoy, and could have been detected in real-time using this new approach.

This example illustrates the potential of our new velocity-field motion-modeling approach to detect anomalous vessel motions among a group of moving vessels. It is relevant to detection of a smuggling vessel breaking away from a nearby fishing fleet, or a terrorist vessel hiding in the presence of pleasure boats in the vicinity of a harbor. Unfortunately, due to a lack of ongoing financial support (aka, "US Congressional sequestration"), this research was terminated prior to conducting further assessment of anomaly-detection performance on this or any other data sets. As implied by the comments of one of our manuscript anonymous reviewer's, we can expect trade-offs between input track-level data quality and anomaly-detection performance. More thorough study should enable the construction of performance ROC curves to help reveal capabilities and limitations of this approach.

4 Conclusion

We have introduced several new concepts and methods for analyzing the motion of multiple entities as they maneuver and execute coordinated group behaviors. We utilize short-time tracks of multiple detections to estimate a locally linear vector field that evolves in time. Thus, long-term group motion is represented, independent of the number of object detections, by an extended track of the group centroid and a single trajectory of the group's relative motion parameters through a 3-dimensional parameter space of group rotation (*R*), expansion (*E*), and deformation (*D*). Learned clusters in this *RED*-space correspond to categories that represent group maneuvers, and temporal sequences of categories represent behaviors. These maneuvers and behaviors can be learned and recognized in real-time using fuzzy pattern recognition (e.g., Fuzzy ARTMAP) in combination with a complex event processor like Seer or Semantic Seer [22]. Importantly, anomalous motions of even a single entity with respect to the group can be easily detected from the residuals between individual vessel velocities and the instantaneous linear field model at each vessel's location. We have illustrated these methods using *OceanWatch* AIS data in the context of a tanker hijacking by pirates in the Gulf of Aden in 2010.

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