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Application of Multi-level Fusion for Pattern of Life Analysis

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Abstract* – *Pattern of Life (POL) analysis constitutes a subset of Activity-based Intelligence (ABI) - understanding those complex spatiotemporal contexts within which entities (e.g., cancer cells, people, etc.) move about and interact, normally-but not always- with a type of recognizable regularity. POL analysis methods are particularly important when attempting to detect and track complex behaviors in stochastic environments such as biological systems or urban terrains, where many interlocking entities coexist and share relationships (e.g., within metabolic pathways, air traffic, ground traffic, shipping environments, businesses, public transit systems, social organizations, etc.). We have developed a Pattern of Life Integrated System (POLIS), which provides a solution combining different but complementary techniques (mathematical and logical approaches) together to form an automated, scalable (i.e., cloud-capable) fusion-based estimation process that can exploit a variety of information sources, including contextual, hard sensor data and other types of soft or human reported data (past reports, existing data models, etc.) to provide POL analyses and alerts which enable efficiencies in analysis and effectiveness in decision support. This approach gives shape to an innovative, unique, and defendable framework for the evolution of an advanced software system applicable to layered POL analysis and enhanced decision-making. This paper provides an overview of the Pattern of Life Integrated System, inclusive of all fusion levels which collectively support the POL analysis. In addition to the system and methodological overviews, a case study is presented which demonstrates the importance and value of the multi-level fusion approach for analyst decision support.

Keywords: Pattern of Life, defining normalcy, low-high level fusion, alerting.

1 Introduction

Pattern of Life (POL) constitute a subset of Activity-based Intelligence (ABI) - understanding those complex spatiotemporal contexts within which people (as cognitive actors) move about and interact, normally with a type of recognizable regularity. POL analysis methods are particularly important to understand when attempting to track complex human or other entity behaviors in stochastic environments such as biological systems or urban terrains, where many interlocking entities coexist and share relationships (e.g., within metabolic pathways, air traffic, ground traffic, shipping environments, businesses, public transit, social organizations, etc.).

Normality is the camouflage of insurgencies. By hiding among the civilian population a militarily inferior insurgent force gains significant advantage against a conventional adversary. The Chinese communist leader Mao Tse-Tung in his renowned book *On Guerilla Warfare (1937)* coined a well-known analogy concerning the inherently symbiotic relationship between a civilian populace and an insurgent force. Mao likened the guerilla fighter to a "fish" and the civilian populace was the "sea" in which he swims. Moreover, the advantages gained by "blending in" have played out across multiple continents, cultures, and conflicts as diverse as our own American Revolution to current day conflicts being fought in Syria, Iraq and Libya. Add to this formidable guerilla tactic a 24 hour news cycle, the internet, and social media providing access to virtually every corner of the globe and the need to provide a counterbalance is clear.

For this reason, accurate and responsive POL analytics are a critical enabling capability for maritime forces responding to short fused crisis events. Defense and security planners have anticipated a growing likelihood of instability in global littoral areas due to population migration patterns away from rural areas and towards more urbanized enclaves which are predominately located within 250 miles of the coast. Maritime commanders and operational planners require capabilities to analyze data obtained from a wide spectrum of traditional and non-traditional sensing capabilities in order to quickly build actionable and predictive battlespace knowledge across a wide range of factors affecting the operational environment. Prime examples include the accurate identification of established Lines of Communication for foot and vehicular traffic (including waterborne vessels) and understanding local norms for commerce, recreation, and religious activities. Additionally, remote trans-border routes are of significant interest when smuggling and foreign intervention from neighboring territories are providing key logistical support for insurgent military operations.

The ***Pattern of Life Integrated System*** (POLIS) presented here provides a solution that combines different but complementary techniques (mathematical and logical approaches) together to form an automated, computationally-scalable (i.e., cloud-capable) and domain-scalable fusion/estimation process that can exploit information from sensor systems and other types of "softer" data (past reports, existing data models, etc.) to provide POL normalcy definitions and pattern estimates that enable efficiencies in analysis and effectiveness in decision support. Our effort gives shape to an innovative, unique, and defendable research framework for the evolution of an advanced software system applicable to layered POL analysis and enhanced decision-making.

The remainder of this paper is organized as follows: Section 2 provides background on the area of POL analysis, Section 3 develops a formal definition of patterns of life, Section 4 identifies the need for information fusion processing to support POL analysis, Section 5 surveys methods for capturing POL normalcy definitions, Section 6 presents an example use case for the pattern of life integrated system and Section 7 presents conclusions and areas for future work.

2 Background

Developing patterns of life requires an understanding of relationships between various entities and their activities, behaviors, and transactions, and thus imputes a relational focus onto the requirements for analysis processes [1]. Our search yielded relatively few pertinent citations for works addressing the ontological or otherwise foundational ideas about the POL concept. The edited text [2] has some relevant chapters addressing the ontological aspects of actions and activities; Chapter 1 of [2], by E. J. Lowe argues: "Any comprehensive theory of action should have something to say about the ontology of actions", a statement consistent with the POLIS goals. This interesting chapter discusses the idea of agents—that perform actions—and also the notions of intentionality in action, and whether events and actions are equivalent, and also the issue of causation of actions. A possible complex activity taxonomy is offered in [3] that nominates six classes as in Figure 1:

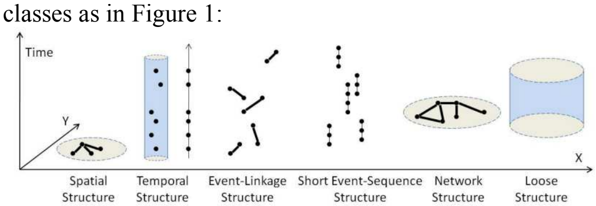

Figure 1 – Activity Structures Making up Complex Activities (from [3]).

A few of the approximately 20+ references reviewed are in [4], [5] that introduce yet other issues regarding the formal specification of activities such as the temporal aspects of actions and activities. All of the points in these references are helpful toward understanding the features of POL-like concepts and components but there are very limited works that formally expand on the ontological foundations of the POL concept. Our work toward the formal specification of POL concepts within a common semantic model, including the derivation and storage of normality and abnormality conditions is presented subsequently.

3 Defining Patterns of Life

As previously mentioned, the concept of Pattern of Life (POL) is somewhat ill defined in military circles, so we have attempted to provide some ontological thought about it in order to better provide a formal description of what it is and what it entails. A POL can be defined as *a logical representation of a spatiotemporal state of affairs*. This definition draws from the naturalistic ontology writings of Edmund Husserl, Franz Brenatno, Adolf Reinach and other turn-of-the century philosophical writers. POL is logically represented often as spatial or temporal tracks (geometric patterns of spatial locations or temporal patterns of timestamps and durations), meaning they are logical representations of entities moving within spatial regions over time. There is normally an added notion of *frequency* of the spatiotemporal patterns, which provides a logical sense of normalcy. A POL is, in this sense, a complex relational type of entity that entails a certain form of logical judgment – meaning, the pattern can be captured and described formally or represented in a computational manner. The types of patterns that are represented in POL often provide a certain form of normalcy through a type of repetition. In this sense, patterns occur again and again over time, often occupying similar temporal durations or spatial patterns of movement – making formal treatments of POL especially informative for activity-based intelligence (ABI). This is important to consider when understanding the use of POL for military applications, since one's enemy can exploit these patterns in a way that provides them with the ability to move about in a more undetected manner – through utilizing common patterns that are part of the normal state of affairs of a given environment. It is important to note however that frequency alone is not an indicator of normality; other criteria must be satisfied as well that permit such labeling.

Often times, when the pattern of normalcy is disrupted, one can then detect an *anomaly*. Anomalies represent a break in the pattern of normalcy pertaining to spatiotemporal patterns. Anomalies are often of interest for analysts studying POLs, but they only exist secondary to establishment of normal patterns of behavior. Therefore, it is important to first understand the normal states of affairs of an environment and provide a proper logical and statistical classification schema to capture them and use them for computations.

A proper ontological schema for POL includes a variety of classes and subclasses of entities, various attributes of those entities, and numerous complex relationship types –

all of which, when combined serve as a normalcy model that captures the logical and/or statistical framework for a complex spatiotemporal state of affairs (Figure 2). Here one can see certain items pertaining to the POL of a ship, which has a complex set of patterns surrounding its spatial movement and activities taken over time.

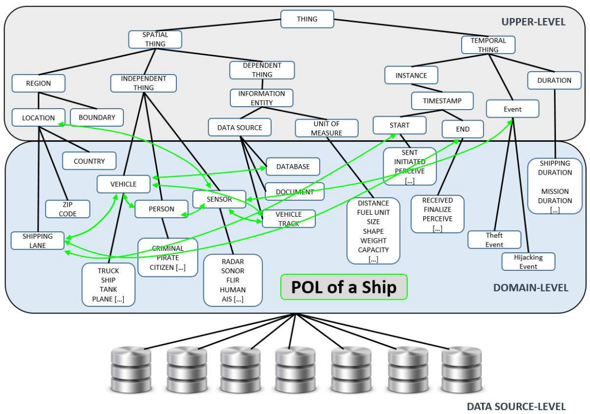

Figure 2 – Pattern of Life of a Ship Spanning Many Ontological Concepts.

The hierarchical class structure represents a taxonomy of items that serve as the background for a ship's POL. The green lines represent various complex relationships within the ontology that link together those classes of items – thereby forming a variety of triples related to the ship's POL in terms of movements, sensing capabilities, locations such as tracks, etc. Using this type of classification schema, along with other visualization and computational techniques (maps, tracks, images, signals, text-based data, etc.) it is possible to construct a complex ontological picture of an entity's POL that allows for advanced logical and mathematical reasoning to be carried out over and against that model. The entities in the ontology represent classifications, attributes and relations – which can be thought of as *features* of a given entity, environment, etc. In this sense, one can determine the patterns of space and time that a given entity will utilize in the course of its "normal" behaviors. Taking that reasoning further, one can thereby also understand anomalous behaviors that break from the patterns at hand.

An important research approach we have taken for our ontology creation is borrowed from advances in Gestalt Psychology – which deals with the concepts of *foreground* and *background* that we have applied to data modeling and data science applications [16]. In POL, the objects of interest (persons, vehicles, spatial regions, etc.) exist as foreground against a contextualized background – normally considered as the environment. We utilize a Basic Formal Ontology (BFO) [20] approach to POL which classifies space and time in appropriate manners, making it easier to draw out and specify the relevant states of affairs that construct entities performing their patterns within their surroundings. A proper metaphysical classification of this nature aligns itself well for a multitude of data fusion cases as described in [6], [7], [8] where the authors apply principles of BFO, Gestalt theory and formal classification schemata to high-level fusion processing for a variety of applications related to intelligence analysis (as is the case with POL).

We have identified the definition of entity POLs within a common semantic model as imperative for the definition and sharing of normalcy models and anomalies detected within an evolving hard+soft evidential knowledgebase. Toward this semantic definition we have developed a methodology for the creation of POL concepts within the ontology, which identifies relationships among the POL and "normalcy dimensions" in the ontology. Normalcy dimensions identify the significant factors or features in deriving and reasoning over normality and abnormality for a particular POL. Logical rules on the values of these normalcy dimensions provide a basic alerting capability in POL analysis (e.g., indicating maximum vessel speeds by vessel type). (Such rules are easiest to form when they can be based on physical constraints but can be much harder to define for other frameworks such as socio-cultural rules.) By encoding POLs within the semantic model, we also enable the POL-centric semantic visualization of POL analysis alerts within a semantic interface (see Section 6 for an example use case). This semantic interface provides the UI layout and widgets necessary for the effective analysis of normalcy dimensions and alerts.

4 Information Fusion Support for POL

A typical question when addressing the issue of framing any estimation problem (we see Information Fusion as, centrally, an estimation process) is to ask: "Where does the problem start?" Patterns can be seen as derived from the already-labeled pattern components—the nodes and arcs of a graph, in effect (this excludes other influences such as context for now). This problem then requires developing a sense of structure toward pattern-labeling, e.g., spatio-temporal structure or structure in the sense of some other parameter such as complexity. However, if "the problem" starts with more fundamental data—say observational data—then there is a need for a layered approach to the IF process that addresses the process of estimating first the labels and attributes of the nodes and arcs upon which and from which the pattern characteristics and labels are derived. In the context of the JDL Model of IF, there is a need for a multi-Level collection of estimation operations.

It can be asserted that the IF community has not carried out much research that addresses POL estimation [22]. There are some publications that have addressed some of the types of problems this paper is focused on, and the methods studied there are summarized below [22]:

Probabilistic plan recognition

- Probabilistic attributed graph matching
- Probabilistic attributed-structural pattern consistency
- Relational Dynamic Bayesian Networks
- Assignment algorithms

- Hidden Markov methodological variants
- Entity-Relation Models
- Relational Particle Filter
- Constraint-based pattern mining

Note that these methods are largely of the type mentioned above that rely on already-labeled pattern components. In the research area of Ambient Intelligence aka Pervasive Systems, Ubiquitous Computing where “Activities of Daily Life (ADL)” are of concern, the estimation of such ADL patterns (a form of POL’s) is instead derived first from the sensor arrays in the domain environment, i.e., starting instead by addressing the problem of estimating the pattern components and then the patterns are derived as a secondary step.

So the extent of IF methods that will be required for any POL problem is related to the way the problem will be structured. It can be asserted with confidence that for any modern problem, there will be a need for “Hard + Soft” IF [23], the inclusion of which escalates the complexity of solution-formation considerably.

5 Defining Normalcy

While not much prior work has not been explicitly defined as “pattern of life” or “rhythm of the city” analysis, we see this emergent topic as an amalgamation of numerous historically well studied fields. These fields fall broadly within the machine learning and artificial intelligence domain, where predictive models often rely on a definition of historical data or expectation to form their predictive conclusions. Included in the historical fields relevant to POL analysis are the topics of: activity recognition [9], [10], trajectory classification [11], landscape/terrain monitoring [12], [13], link prediction in social networks [14], [15], among others.

Within and across these varied topical areas, some common data modalities and mathematical techniques are used as shown in Table 1 and Table 2 respectively. The definition of normalcy is a precursor to performing POL analysis. A normalcy definition may take a variety of forms depending on the context of the POL it seeks to define. POLIS focuses on three major classes of normalcy definition including: feature-based, trajectory or tracking-based and general graph data.

Table 1 – Data modalities considered by existing POL methodologies.

	Data Sources Considered				
Paper Title	AIS	FMV	Radar	Text	WAMI
Anomaly Detection for Sea Surveillance [24]	X				
Context-aware tracking with wide-area motion imagery [25]					X
Detection of Anomalous Trajectory Patterns in Target Tracking via Stochastic… [26]		X	X		
Determining Intent using Hard/Soft Data and Gaussian Process Classifiers [27]					
Human Activity Recognition and Pattern Discovery [28]		X			
PARSEC, an Application of Probabilistic Case Based Reasoning to Maritime Surveillance [29]	X				
Pattern of Life for Radar Port and River Security [30]		X	X		
Proactive Insider Threat Detection through Graph Learning and Psychological Context [31]				X	
Statistical Analysis of Motion Patterns in AIS Data: Anomaly Detection and Motion Prediction [32]	X				
Track Anomaly Detection with Rhythm of Life and Bulk Activity Modeling [33]		X			
Vessel pattern knowledge discovery from AIS data: a framework for anomaly detection and route prediction [21]	X				
Visualization of Vessel Movement [34]	X				

Table 2 – Mathematical approaches applied by existing POL methodologies.

	Technology(ies) Applied											
Paper Title	Bayesian Methods	Conditional Random Fields	Emerging Patterns	Expectation Maximization	Gaussian Mixture Models	Graph Partitioning	Graph Structurual Anomaly	Kernel Density Estimation	Markov Models	Probabilistic Dependency Networks	Psychological Profiling	Radar micro-Doppler
Anomaly Detection for Sea Surveillance [24]				X	X							
Context-aware tracking with wide-area motion imagery [25]												
Detection of Anomalous Trajectory Patterns in Target Tracking via Stochastic… [26]	X								X			
Determining Intent using Hard/Soft Data and Gaussian Process Classifiers [27]	X											
Human Activity Recognition and Pattern Discovery [28]		X	X						X			
PARSEC, an Application of Probabilistic Case Based Reasoning to Maritime Surveillance [29]										X		
Pattern of Life for Radar Port and River Security [30]												X
Proactive Insider Threat Detection through Graph Learning and Psychological Context [31]						X	X				X	
Statistical Analysis of Motion Patterns in AIS Data: Anomaly Detection and Motion Prediction [32]								X				
Track Anomaly Detection with Rhythm of Life and Bulk Activity Modeling [33]				X	X				X			
Vessel pattern knowledge discovery from AIS data: a framework for anomaly detection and route prediction [21]								X				
Visualization of Vessel Movement [34]								X				

6 Pattern of Life Use Case

We have constructed a realistic maritime scenario where the developed POL analysis is imperative in detecting an unfolding terrorist bombing plot. The demonstration simulation is performed within Modus Operandi's MOVIA Platform. MOVIA is a rapid application development platform specifically designed for intelligence-driven threat detection and warning for Big Data streams and repositories. MOVIA provides the ability to explore, analyze and monitor Big Data, predict emerging patterns of threat or opportunity, and provide warnings via a "tap-on-the-shoulder" from an alerting software agent. MOVIA is a highly modular component-based architecture. The application of the componentized architecture provides significant flexibility to the mission, robust solutions and versatility in deployment.

MOVIA is constructed in three main elements: ingest, processing, and user interface (UI). The entire MOVIA Platform System is a component-based system. The cohesive components provide a robust functionality while the loose coupling between bundles provides the flexibility necessary for the system to adapt to its many roles. With varying deployment options from a single node in the smallest configuration to the full enterprise deployment, MOVIA provides the flexibility, scalability, and reliability necessary for any solution.

Simulated scenario data released to the MOVIA ingest process includes streaming AIS readings from both terrestrial and satellite collection assets, sensor coverage context and soft data reports. The scenario begins with the derivation of vessel normalcy within our analyst's area of interest (AOI), the Adriatic Sea[1]. Historical AIS tracks within the AOI are utilized to identify track entry, exit and stationary waypoints, derive voyage lanes and form probabilistic KDE normalcy definitions within each voyage lane (see [21] for a description of the methodology applied).

Given a track-based normalcy definition Figure 3 (subfigure a) which conveys the spatiotemporal characteristics of a vessel traveling between an origin-destination waypoint pair, we are able to calculate the likelihood any streaming AIS track[2] is anomalous and when provided a likelihood cutoff, we are able to classify tracks as anomalous or normal (see Figure 3 subfigure b). The importance of the consideration of the time normalcy dimension is shown in Figure 3 subfigure d. If we were to only consider the spatial characteristics in a normalcy definition, the example track would not appear abnormal. However, when we also take into account the temporal normalcy definition we are provided the conditional probability distribution shown in Figure 3 subfigure c) at time period: $t = 10$. From this temporally conditioned probability distribution we are able to identify the anomaly in this track – i.e., the vessel has not advanced as far as it should have in the track time.

The scenario unfolds as 3 tracks of interest approach the poor coverage area – one each from the Venice and Pula stationary waypoints and one from a southern AOI entry waypoint. As the three vessels enter the poor coverage area their AIS signals are eventually lost at which point the threat level is elevated, however not sufficient to warrant an alert (see Figure 4). As time passes without a signal from the vessel a voyage lane anomaly is detected as it is determined that the Nuran Ana should have left the poor coverage area and reemerged in the AIS stream (see Figure 3 subfigure c). This track anomaly further raises the threat level to a point which is sufficient to trigger an alert event. In addition to the analyst alert (Figure 5), an alert is sent to the inexact graph matching process ([17],[18],[19]) which triggers an alert area restricted graph matching query seeking connections between local vessels and suspicious individuals (e.g., known terrorists, drug traffickers, bomb makers, etc.).

While investigating the initial alert (Figure 5) within the alert page (Figure 6), the graph matching process uncovers a connection between the anomalous ship and a known bomb maker, further raising the threat level. Facilitated by hard+soft association of a vessel in the AIS POL anomaly area, this connection is returned to the MOVIA semantic reasoner which further identifies the anomalous ship track is connected to bomb making dual use material, a cargo ship carrying fertilizer within the same poor coverage area as the bomber connected vessel. This reasoning chain causes another alert to the user (see Figure 7). In clicking on the alert, the user is brought to the alert page (see Figure 8) which explains the reasoning process behind the alert. This page presents brief information on each of the alerting entities (Nuran Ana fertilizer cargo ship, Baka Mbele – Arctic Express crew member, etc.), the subgraph from the cumulative associated evidential data which lead to the alert and provenance information explaining the supporting data and reasoning chain. Links on the alert page can be followed to drill down into alert entities and events (e.g., to bring up the Nuran Ana semantic wiki page). Ultimately these alerts and alert/entity pages provide the analyst the actionable intelligence required to intervene in the execution of a potential bomb threat as indicated by the co-location of an anomalous ship, bomb maker and dual use material (fertilizer).

[1] *A priori* information on AIS collection coverage within the AOI is considered, with a poor coverage area as indicated within Figure 4.

[2] Note – the anomaly detection process is performed incrementally as additional track readings are obtained. Sensor coverage is taken into account via dynamic lost object thresholds derived from the coverage areas.

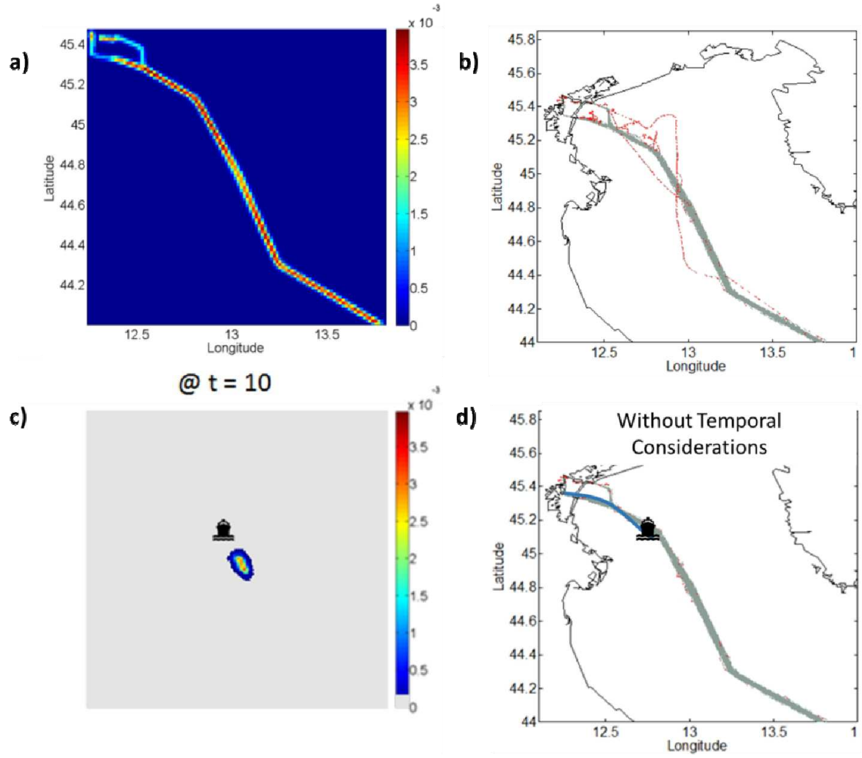

Figure 3 – Track-Based Normalcy Use Example. Subfigure a) Displays the KDE-based Normalcy Definition for the Shipping Lane from [21] b) Displays Anomalous Tracks as Determined by the KDE Normalcy Anomaly Detector, c) Displays the KDE Conditional Probability Distribution at Time Step 10. (Note – the Inclusion of Time Identifies the Vessel as "behind" the expectation for this shipping lane), d) Displays the Difficulty in Discerning this Anomaly in a Strictly Geospatial Approach. Figures adapted from [21].

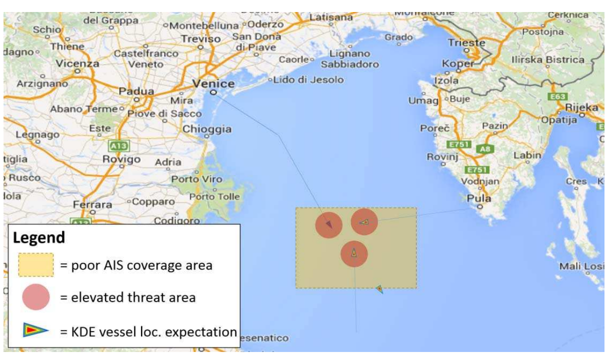

Figure 4 – Example Scenario Tracks.

Figure 5 - MOVIA Alert on Vessel POL Anomaly.

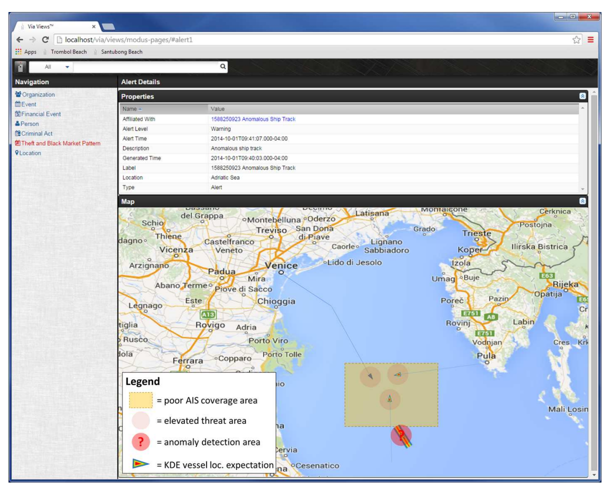

Figure 6 – MOVIA Views Vessel POL Anomaly Page.

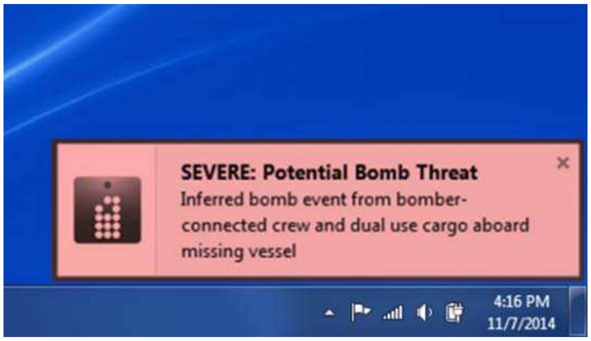

Figure 7 – Potential Bomb Threat Alert.

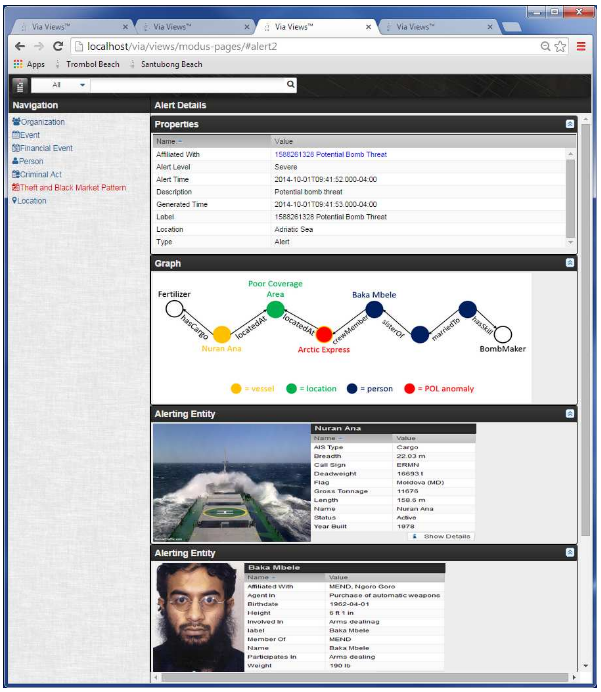

Figure 8 – Potential Bomb Threat Alert Page.

7 Conclusion

This paper presented a Pattern of Life Integrated System (POLIS) including a use case illustrating the importance of a multi-level fusion and multi-analytic framework for pattern of life analysis. The demonstration scenario simulated within Modus Operandi's MOVIA Platform utilizes processes for: 1) the derivation of normalcy definitions, 2) the ingest of natural language reports, 3) the ingest of AIS track data and sensor collection coverage context, 4) hard+soft data association and fusion, 5) POL anomaly detection, 6) threat modeling and alerting, 7) inexact stochastic graph matching, 8) semantic reasoning and 9) semantic visualization. This multi-process demonstration highlights the ability of POL analysis to form the basis for a higher-order man-machine sensemaking paradigm, within which semantic and statistical processes are unified. We note that a research area of great importance for pattern of life analysis which was not covered here includes the identification, quantification and resolution of normalcy model drift. These issues will be considered in future work.

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