Biologically-Inspired Approaches to Higher-Level Information Fusion

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Abstract – Contemporary situational awareness problems such as automated normalcy learning for anomaly detection and motion behavior prediction are addressed with biologically-inspired processing, representation, and learning approaches. Issues and challenges are discussed and our responses to them described. Relatively simple neural principles provide considerable power in providing capabilities required to learn models of normal motion behavior and utilize those models to identify unusual behavior or determine the most likely future behavior of objects of interest.

Keywords: Higher-level fusion, situation awareness, learning, prediction, neural networks.

1 Issues

Situation awareness and threat assessment are major objectives of higher-level fusion systems. Effective and comprehensive achievement of these objectives remains elusive. Nevertheless, considerable progress has been made on several sub-problems. Among these are the detection of unusual behavior of objects of interest and prediction of their future behavior.

The former requires answers to questions such as: What constitutes normal behavior? On the basis of prior behavior, is current behavior normal? If the current behavior is not normal, how far does it deviate from normalcy and why is it anomalous? Relevant questions for the latter include: Given behavioral history and subject to current behavior, what future behavior is expected? Is current behavior reasonable (i.e., within predicted ranges) given prior behavior?

Numerous levels of analysis can be employed when developing approaches to providing operators/analysts with automated assistance in answering such questions. These range from short-term events (represented by current object state in relation to its environment) through longer-term behaviors (such as a sequence of maneuvers or other behavioral events). Discovery of principles and algorithms that can be leveraged to address multiple (or all) levels is of particular value towards solutions that are seamless and self-consistent.

The remainder of this paper identifies some of the challenges encountered during our efforts to address these questions, provides a brief overview of our approach and capabilities to date, and contemplates how our approach can provide the basis for further progress in developing higher-level fusion capabilities.

2 Challenges

What is normal may differ between contexts. The possible combinations of conditions creating different contexts are numerous enough to defy efforts to manually define (and subsequently use in real-time) a complete set of rules to cover all cases. A continuously learning, adaptive system holds promise for dealing with such complexity without requiring unrealistic involvement of expert input on a frequent basis.

The environments in which behavior is being assessed are also often non-stationary, indicating the need for an adaptive system that operates well when confronted with such difficulties. The complexity of the contextual-specificity of normal behavior and the non-stationary nature of the target environment indicate that efforts based solely on a priori models of typical behavior (that are necessarily domain specific) will not be satisfactory as a general solution. Moreover, severely constrained numbers of operators/analysts, in combination with massive amounts of data, prevents timely labeling of events to provide ground truth for any normalcy discovery endeavors. This can be a severe constraint that disqualifies many approaches as suitable candidate solutions. An additional challenge is that the environments under consideration here provide limited training data in that abnormal behavior is (by definition) rare.

3 Retrospectives: Implementations to date

In response to these challenges (amongst others), and encouraged by the success of similar approaches to lower-level fusion [1, 2], we have adopted an adaptive, data-driven approach that is strongly motivated by biological
and cognitive principles of learning and information representation. Consistent with the way that humans learn and categorize events, normalcy models are updated and learned incrementally as new data becomes available. Supervision, in the form of labeled teaching input, can be taken advantage of, but is not necessary for effective learning. This is particularly important given the dearth of human operators noted earlier. It is important that the learning system operates autonomously so as to not make demands on already busy operators.

Primarily for tractability, we have focused our research and development efforts on kinematic normalcy modeling in the maritime domain. Additionally, detection of unusual vessel activity is an important homeland security maritime domain awareness (MDA) objective. Hence, the following presentation of our major foci will utilize maritime examples [see also 3, 4].

One goal of our system is to continuously learn normal vessel behavior and detect anomalies (i.e., deviations from normalcy) with little or no human supervision. Our learning algorithm is based on Hebbian associative learning [5]. Learning of normal events can be achieved via training with a set of observations that are known to reflect routine activity. Ideally the observations would contain sufficient numbers of exemplars from all the contexts in which the system will be required to operate. However, this is not mandatory because our learning paradigm can adapt at a later point in time, either autonomously or via operator input. As normalcy is learned, new observations can be judged for normalcy. Those events considered unusual can then be flagged as alerts to cue human operator attention. Normalcy models are learned for individually identified vessels as well as for classes of vessels. Our learning system is capable of discovering normalcy for a variety of local contexts that are relevant to vessel behavior.

It is not sufficient to merely identify instances of anomalous behavior. It is important to be able to determine why and how a particular event deviates from normalcy. Our learned representations inherently support extraction of this information – the level of deviance can be established for each feature dimension within the normalcy model(s). To the extent that a particular behavior event deviates sufficiently from several relevant models, the deviation information for each violated model can be provided as part of the explanation of an anomalous event.

Another goal of our system is to be able to predict the future position of a vessel given its current behavior (location and velocity). Essentially, this involves associative learning of links between behavioral events [5]. It is crucial that learning occurs incrementally in order to allow the system to take advantage of increasing amounts of data without having to take the system offline, while adapting to changing behavior patterns automatically.

Our associative learning algorithm has a number of attractive properties for the current application. First, more frequent combinations of source and target locations are rapidly learned, as revealed by larger weights. Second, random/infrequent associations will cause learning when they occur but will also be unlearned through weight decay, when they do not occur. This property also provides noise tolerance. Third, the system is able to automatically adapt and track changes in behavior over time. Fourth, the system is also able to maintain multiple sets of models for alternating operating conditions, for example, to capture seasonal differences or other factors. Fifth, the learning is entirely unsupervised, and requires no operator intervention.

Our system utilizes the predictions to for alerting on anomalous activity. Consider a particular vessel that produces a current report that triggers learning. This requires the data buffer to contain a report from that vessel when the temporal horizon window opened. This prior report can be presented to the model for the purpose of generating predicted future locations. If the current location is not among the predicted locations, then an alert can be raised. Such an alert indicates that the vessel is now somewhere it wasn’t expected to be on the basis of its prior behavior.

The outputs from the various components of our system are also highly configurable. For instance, they can be provided to other automated fusion components and/or to human operators/analysts. Anomaly alerts, for example, can be displayed to operators who can then determine a course of action and possibly provide feedback to the learning system in the form of alert confirmation or rejection/dismissal. Another option would be to forward that alert information to automated sensor resource management elements. These, in turn, would attempt to task available sensors to gather more information to further evaluate the nature of the triggering behavior and determine the level of threat posed.

The use of the associative learning algorithm of [5] is but one example of leveraging a basic principle for multiple purposes. In [5] the algorithm was developed to learn hierarchical taxonomic links between abstract concepts/labels on the basis of their co-occurrence in the data.

The significant AFOSR-funded basic research sponsorship has been leveraged and enhanced under a number of application-specific MDA programs. We have also successfully employed our approach in land-based situations.

4 Perspectives for the Future

We have employed a variety of biologically-inspired processing, representational, and learning principles to create a highly-configurable, scalable, and extensible system for exploiting track data to learn normal patterns of motion behavior, detect deviations from normalcy, and predict future behavior. These capabilities address a set of
important higher-level fusion problems and provide a solid foundation for further development and application.

Drawing upon the capabilities of neural systems has resulted in a system that operates well when confronted with many of the difficulties associated with contemporary situations for which high-level fusion is required. For example, the approach is not specific for any single domain. The learning and representational capabilities we have developed are applicable across many domains. Through the use of incremental, local learning laws our algorithms operate extremely quickly. This enables millions of reports per day to be processed while producing normalcy models that are both specific to individual (or class group of) actors and adaptive to changing contexts or operating modes. The latter is particularly important in non-stationary environments. The incremental nature of our learning approach obviates the need for off-line batch mode model re-learning that is characteristic of many alternative approaches in order to incorporate new data.

It is important to note that we have not, and did not attempt to, develop a general cognitive architecture to address higher-level fusion as a whole. Rather, we have focused on a relatively small – but nonetheless important – part of the overall problem space. The principles we have identified and the algorithms they have generated have thus far proven quite useful in addressing the problems of normalcy learning, anomaly detection, and behavioral prediction. It is likely that we will be able to further refine our approaches to improve upon their current level of performance and that we will be able to apply these approaches to additional higher-level fusion problem areas.

References


