Methods of Machine Learning for Space Object Pattern Classification

Dan Shen, Jingyang Lu, Genshe Chen
Intelligent Fusion Technology, Inc
Germantown, MD, USA

Erik Blasch, Carolyn Sheaff, Mark Pugh
Air Force Research Lab
Information Directorate
Rome, NY, USA

Khanh Pham
Air Force Research Lab
Space Vehicles Directorate
Kirtland, NM, USA

Abstract – *Space superiority requires space protection and space situational awareness (SSA), which rely on rapid and accurate space object behavioral and operational intent discovery. The analytics required for space object detection, tracking, and pattern classification include machine learning. The development of deep learning (DL) methods shows promise in many areas. In this paper, a convolutional neural network (CNN) classifies the behaviors of space objects for evasive satellite behaviors detection. Additionally, within the Adaptive Markov Inference Game Optimization (AMIGO) engine, a game theoretic approach describes the situation versus a control problem. Using data-level fusion, stochastic modeling/propagation, and DL pattern classification. Numerical simulations demonstrate the advantage of DL methods for space object pattern classification improving from 34% to 98% with training.*

Keywords: *Deep Learning, Image Fusion, Situational Assessment, Knowledge Representation, User Refinement*

1 Introduction

Since space has been accessible, society has become more dependent on space superiority across a broad spectrum of military, civilian, and commercial applications. Since many systems rely on continuity of space operations (e.g., communications, weather prediction), the dependence presents an inherent vulnerability which requires persistent space situation awareness (SSA) [1,2]. Space is considered as an important frontier because information from the space has become extremely vital for strategic decisions. The presence of adversaries in addition to real-time and hidden information constraints greatly complicates SSA. Knowing the locations of space objects from low-level information fusion supports high-level information fusion SSA tasks of sensor, user, and mission refinement [3, 4, 5]. To accurately provide SSA, resident space object (RSO) assessment can be coordinated through a User-Defined Operating Picture (UDOP) [6, 7, 8, 9].

Space superiority requires space protection and awareness, which rely on rapid and accurate space object behavioral and operational intent discovery. Many recent efforts have focused on machine learning (ML) approaches for space operations including Artificial Neural Network (ANN) [10, 11], Support Vector Machines (SVM) [12], reinforcement learning [13, 14], and deep neural networks [15], for behavioral analysis [16] and autonomy [17, 18].

The focus of this paper is to develop a stochastic approach for rapid discovery of evasive satellite behaviors utilizing methods of ML. The design of the innovative decision support tool has numerous challenges: (*i*) partial observable actions; (*ii*) evasive resident space objects; (*iii*) uncertainties modeling and propagation; (*iv*) real-time requirements, and (v) computational intractable algorithms.

Space defense analysis and mission trade-off studies are vital for the success of space-borne operations. Space object tracking algorithms [19,20,21,22,23] can be compared based on gathering data to track satellites, debris, and natural phenomena (e.g., solar flares, comets, asteroids). Tracking is associated with sensor management to point sensors for observations [24,25] and determine the situation and threat awareness [26,27]. SSA enhancements include models (e.g., orbital mechanics), measurements (e.g., space-based optical sensors), computational software (e.g., tracking), and application-based systems coordination (e.g., situations). For example, *game-theory* approaches for SSA allow for pursuit-evasion analysis [28,29,30,31,32]. SSA tracking includes understanding of orbital mechanics, mission policies, and technical purpose [33, 34, 35].

SSA challenges also include communications issues such as detections [36, 37], waveform selection [38], and attack mitigation [39,40,41], from which game-theoretical methods support cyber awareness [42]. Utilizing multi-coordinated systems [43,44], context [45], and space environment models [46], support advanced SSA data fusion [47], tracking [48], and awareness [49].

This paper develops and implements a solution called *Adaptive Markov Inference Game Optimization (AMIGO)* for rapid discovery of evasive satellite behaviors. AMIGO is an adaptive feedback game theoretic approach as shown in Fig. 1.

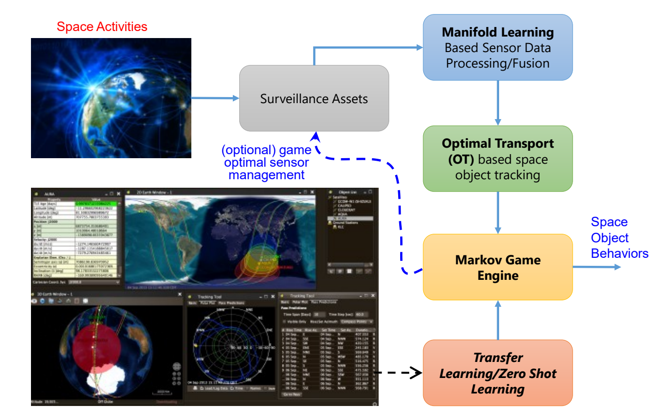


Figure 1. System Architecture of the AMIGO.

AMIGO gets information from sensors about the relations between the resident space objects (RSOs) of interest and ground and space surveillance assets (GSAs). The relations are determined by both the RSOs and GSAs. Therefore, AMIGO represents the situation as a game utilizing data-level fusion, stochastic modeling/propagation, and RSO detection/tracking [50] to predict the future RSOs-GSAs relations. To determine the space object patterns, both manifold and deep learning methods are developed.

The AMIGO game engine also supports optional space pattern dictionary/semantic rules for adaptive transition matrices in the Markov game [51]. If no existing pattern dictionary is available, AMIGO builds an initial pattern and revises it during the game reasoning. The outputs of the AMIGO reasoning include two kinds of control methods: (i) processing of GSA measurements and (ii) localization of RSOs. The two sets form a *game equilibrium*, one for surveillance asset management and the other for the estimation of RSO behaviors. In this paper, we will focus on the use of training data generation and ML (e.g., CNN) pattern classification.

The paper is organized as follows. Sect. 2 presents the overall system design for AMIGO. The Markov game and satellite maneuvering are detailed in Sect. 3. The machine learning approach for space behavior detection is shown in Sect. 4. Sect. 5 presents some numerical results and analysis. Finally, conclusions are drawn in Sect. 6.

2 AMIGO Overview

The Markov game engine is the central piece of AMIGO to detect *unknown* patterns of evasive space objects. Since the patterns are unknown, there is no training data available. The Markov game engine leverages transfer learning and zero-shot learning to recognize unseen classes with available training data from another set (i.e., simulated data) of seen classes. The knowledge transfer results via an intermediate semantic embedding (e.g., attributes) shared between seen and unseen classes using manifold learning. The manifold learning can reduce the dimensionality of the sensor data and scale down the object detection and tracking difficulties and enable the *rapid* detection of space object behaviors. To handle the *uncertainties* in this problem, we use the $\mathbb{R}^5\times\mathbb{C}$ coordinate system and *optimal transport (OT)* based filtering techniques. The key features of the proposed AMIGO are list as follows:

(1) *Markov Game* – Conflicting space situations are reasoned by a Markov game structure [52, 53, 54], where system states are represented by distributions instead of deterministic values.

(2) *Uncertainty modeling and propagation* – representation of uncertainties as a product of independent Gaussian and Von-Mises distribution for both measurement noise and initial condition uncertainty, which are defined on cylindrical manifold $\mathbb{R}^5\times\mathbb{C}$ [55]. Relaxed synchronization for uncertainty propagation with guaranteed convergence.

(3) *Optimal Transport based Tracking of Space Objects in Cylindrical Manifolds* – The proposed optimal transport (OT) [56,57] is more accurate than the ensemble Kalman filter (EnKF) for space object tracking problems. In addition, OT is distribution agnostic and it is more general than algorithms that assume uncertainties in $\mathbb{R}^n$.

(4) *Pattern Dictionary and Semantic Rules* – The machine learning utilizes the intermediate semantic layer from zero-shot learning [58]. In the AMIGO solution, the semantic layer will dynamically and adaptively change the transition matrices in the Markov game. This semantic layer depicts the relationships between features, attributes, and classes. It can also speed up the Markov game reasoning.

(5) *Course of Actions for intent modeling* – The RSO's behavioral intent is modeled by a course of action (CoA) [59], which tells what the RSO is doing and what the RSO might do in next several steps.

(6) *Manifold learning for data-level sensor fusion* – The sensor raw data are usually high dimensionalities. Since the measurement data streams are reflections of the targets of interest, whose states can be determined by only a few parameters, it is reasonable to assume the measurement domain has a low intrinsic dimensionality. Dynamic data driven applications systems brings together high-dimensional modeling with low-dimensional measurements [60,61]. Manifold learning algorithms [62,63] reduce dimensionalities and save the communication bandwidth [64].

(7) *Deep learning for decision-level fusion* – Using the data from the manifold learning track outputs, AMIGO learns the normal pattern behaviors and classifies them with semantic labels for tracking and identification [65, 66, 67, 68, 69]. From the normalcy results, anomalies can be determined from new track behaviors that do not meet the appropriate decision thresholds.

The emulated satellite positions are used as measurements, whose results will be used to perform multiple space object tracking to refine the position estimates. Then the tracking estimates will go to the space object maneuver detection and collision alert. The satellite maneuver commands will be translated to platform commands to emulate space object movement, course of actions and sensor management [70,71]. The commands can be coordinated over cloud [72,73,74] and fog networks [75,76]. AMIGO determines to forms of a game equilibrium, one for space surveillance asset management and the other for RSO behavior estimation.

3 Markov Game in SSA

A stochastic game [53], introduced by Lloyd Shapley in the early 1950s, is a dynamic game with probabilistic transitions played by one or more players. The game is played in a sequence of stages. At the beginning of each stage the game is in some state. The players select actions and each player receives a payoff that depends on the current state and the chosen actions. The game then moves to a new random state whose distribution depends on the previous state and the actions chosen by the players. The procedure is repeated at the new state and play continues for a finite or infinite number of stages. The total payoff to a player is often taken to be the discounted sum of the stage payoffs or the limit inferior of the averages of the stage payoffs. Stochastic games generalize both Markov decision processes and repeated games.

A Markov (stochastic) game [53] is given by (*i*) a finite set of players N, (*ii*) a set of states, S, (*iii*) for very player $I \in N$, a finite set of available actions D^i (we denote the overall action space $D = \times_{i \in N} D^i$), (*iv*) a transition rule q: $S \times D \rightarrow \Delta(S)$, (where $\Delta(S)$ is the space of all probability distributions over S), and (*v*) a payoff function r: $S \times D \rightarrow R^N$. The Markov game engine uses the specific information of event extraction.

A visual depiction of state of a simple game is presented in Fig. 2. There are two players and each player has two actions. The arrows in Fig. 2 show the possible transitions from one state to another. The red color indicates that only player 1 changes the strategy while blue color denotes only player 2 adjust the strategy. The green colored states denote both players maneuver.

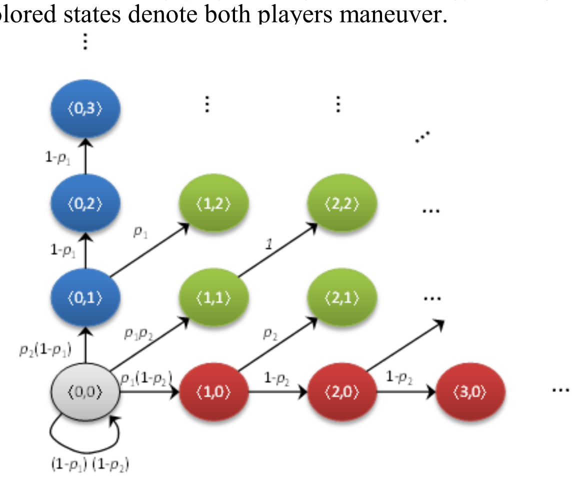


Figure 2. Diagram of States in a Markov Game

AMIGO uses a two-player Markov game to investigate the sensor management for tracking evasive space objects. Whether deliberate or unintentional, some of space objects may cause confusion to observers (satellites) by performing orbital maneuvers. Generally, the space-object tracking problem can be modeled as a one-sided optimization (optimal control) setup or a two-sided optimization (game) problem. In the optimal control setup, the states (positions and velocities) of space objects are computed (filtered) based on the sensor measurements. However, the optimal control approach does not consider the intelligence of the space objects that may change their orbits intentionally to make it difficult for the observer to track it. The Markov game approach provides a method to solve the SSA problem, where the evader will exploit the sensing and tracking model to confuse the pursuer by corrupting their tracking estimates, while the pursuer wants to decrease the tracking uncertainties. The uncertainties are modeled based on the tracking entropy.

The PE game approach [77,78] for informational uncertainties with a scenario of two satellites: a space-based surveillance system (SBSS) Low Earth Orbit-LEO satellite (pursuer) [79] and Geostationary Earth Orbit-GEO (evader) was developed using a space based optical (SBO) sensor measurement model (Fig. 3). The bistatic solar angle θ is defined as the angle of the line from the space object to the sun and the line from the object to the SBO. The lighting condition is strong when the angle is small and it is weak when the angle θ is large. When θ is large, the space object is hard to be observed due to saturation. The scenario is shown in Fig. 4, where the red line indicates the direction of sun light, green color is for the GEO orbit with maneuvers, blue color for SBSS orbit, and pink lines indicate when the SBO sensor resource is used to track the GEO (use the sensor data to lower the uncertainty).

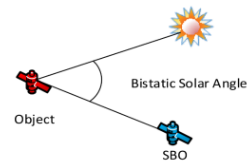


Figure 3. SBO with a Bistatic Solar Angle

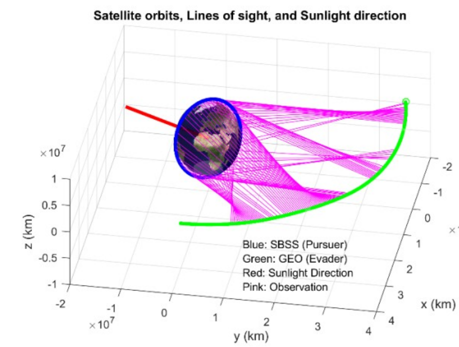


Figure 4. SBSS and GEO under the game-theoretic sensor management and maneuver strategies

The tracking results are shown in Fig. 5 with the extended Kalman Filter (EKF) and cubature KF (CKF) trackers which converge with intermitted measurements. Nonlinear trackers [80] have increasing errors during the no-measurement period. The evader's maneuver motions increase the tracking errors while the sensor measures can reduce the informational entropy [81].

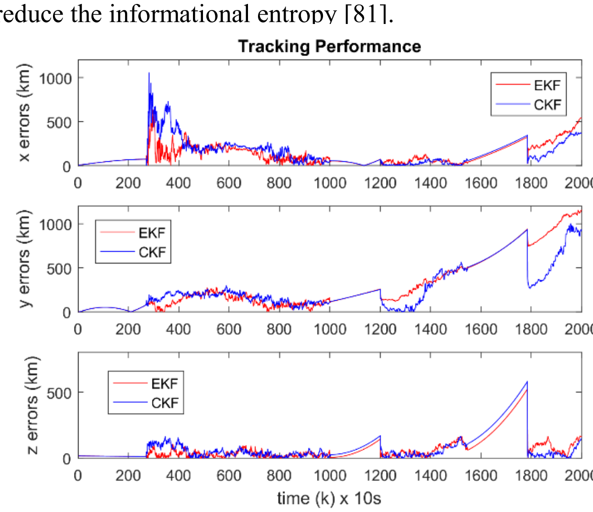


Figure 5. The tracking performance with Markov game theoretic maneuver strategies

The game controls are shown in Fig. 6. The bottom zoom-in view demonstrates that the pursuer saves the sensor resources while keeps the tracking uncertainties in a desired level. This conclusion can also be shown in Fig. 7, where the information gains are displayed. It is shown that when the potential information gains are bigger; the pursuer will spend the sensor resources to make measures.

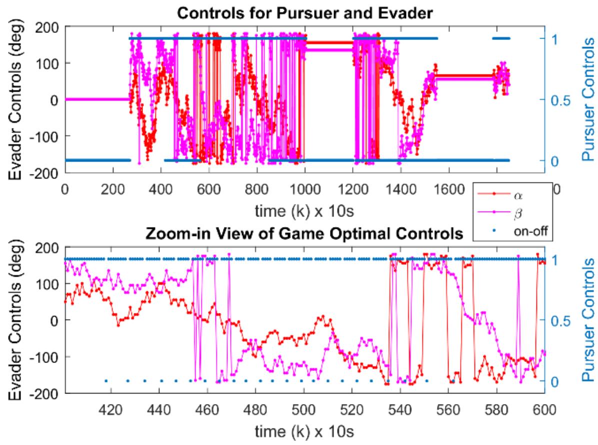


Figure 6. The satellite maneuver directional controls based on the PE game solutions

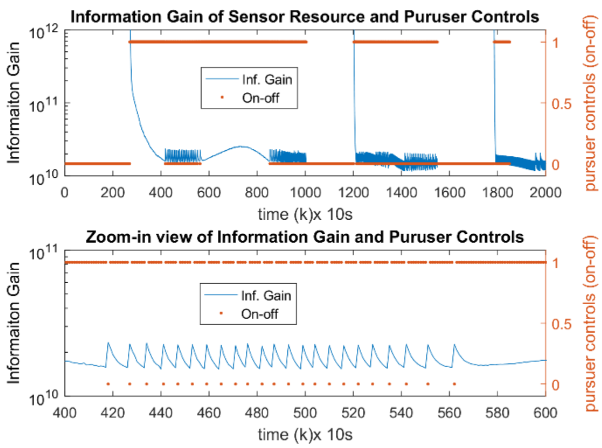


Figure 7. Information Gains and Pursuer's Game Theoretic Controls

4 Machine Learning Based RSO Behavior Pattern Classification

4.1 Machine Learning Methods

This section presents the AMIGO ML design, which detects the resilience space object (RSO) behavior pattern through fusing heterogeneous data from multiple sensors - such as position of RSO relative to the observing station, velocity, orbital energy, and angular momentum, etc. The data set will be studied and analyzed in the feature selection model before being transferred as the input for the reinforcement learning-based [82] jammers, interferences deep classification [83]. The model can be trained off-line, and the well-trained model will be deployed in the real application stage. Also, the proposed classifier can also be updated through online-policy learning, which can help improve the system robust to the newly unknown behavior pattern.

Fig. 8 shows the architecture of the proposed RSO behavior pattern classification. The whole system is separated into (a) offline - Modeling RSO Behavior Pattern and (b) online - Monitoring RSO Behavior Pattern.

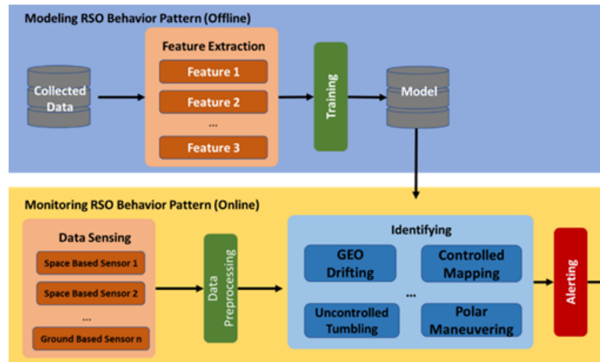


Figure 8. RSO Behavior Pattern Classification

In the offline part, *Modeling RSO Behavior Pattern*, the system trains a classifier model using machine learning techniques based on the collected data, which could identify specific types of RSO behaviors. In the feature extraction, effective features are extracted from multiple sensors. Afterwards, the features are trained in the training and a classifier model is generated which can realize fine-grained identification. The online part, *Monitoring RSO Behavior Pattern*, the system senses real-time RSO dynamics to detect and identify abnormal behavior patterns. If any of the abnormal behaviors are identified, a warning message would be triggered to situation enhance awareness [84].

The ML classifier for the given task has the following ideal properties: (a) scalability, (b) ability to incorporate complex, heterogeneous input data, (c) predictive power, (d) stability with respect to data perturbations, and (e) interpretability. Typically, not all of these five properties can be satisfied to the same extent, and a suitable balance is required. Below, we present a machine learning method based on CNNs.

4.2 CNN-based Framework

Convolutional Neural Networks (CNNs) are very similar to the traditional Neural Networks as shown in Fig. 9.

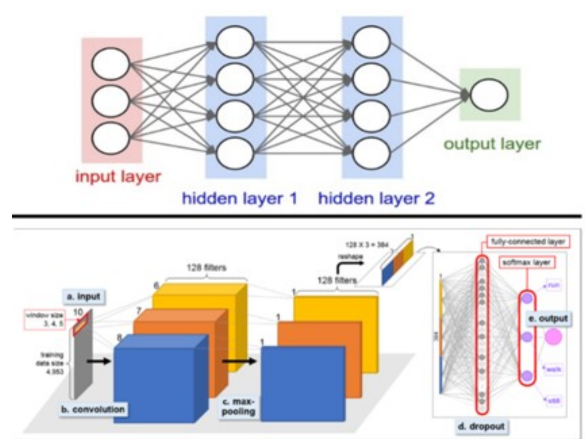


Figure 9. The Framework of the CNN

In the regular neural network, neural networks receive an input and transform it through a series of hidden layers.

Each hidden layer consists of a set of neurons, where each neuron is fully connected to all neurons in the previous layer. Neurons in a single layer function are completely independent and do not share any connections. The fully connected layer is called the “output layer” representing the class scores.

The drawbacks of regular neural nets are that they don’t scale well to full images. Take an image of size 18×18×3 for example, a single fully-connected neuron in a first layer of a regular neural network should have 18×18×3 = 972 weights. As image size goes up, it will result in large number of weights needed tuned, which may lead to the overfitting issue.

Fig. 9 (top) is the traditional neural network and the Fig. 9 (bottom) is the Convolutional Neural Network. A simple CNN [85] is a sequence of layers, and every layer of a CNN transforms one volume of activations to another through a differentiable function. The CNN consists of *convolutional layer, pooling layer, and fully connected layer*. CNNs take advantage of the fact that the input consists of features, which constrain the architecture in a more sensible way. In particular, unlike a regular neural network, the layers of CNNs have neurons arranged in 3 dimensions: *width, height, depth*.

CNNs have achieved great success in the image processing and computer vision [86, 87, 88] and support efficient information management [89, 90]. A CNN works by moving small filters across the input dataset. This means the filters are re-used for recognizing patterns thorough the whole input data. The CNN is much more powerful than the Fully-Connected networks (FCN) with the same number of variables, and in turn, makes the Convolutional networks faster to train.

The CNN is made up of neurons that have learning weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network still expresses a single differentiable score function - from the raw image pixels on one end to class scores at the other. And they still have a loss function (e.g., SVM/Softmax) on the last (fully-connected) layer for the RSO behavior pattern prediction.

AMIGO uses CNNs to classify the RSO observation data. Comparing to the traditional approaches, the proposed CNN can produce a new way of processing RSO observations where quick determinations of RSO classes are made possible directly from the observational data. Python and TensorFlow [91] are used as the simulation environment for this work. The training of the CNN classification approach is computationally expensive, but it is expected that once trained on a larger dataset, the approach can outperform traditional methods while providing a computationally efficient classification model.

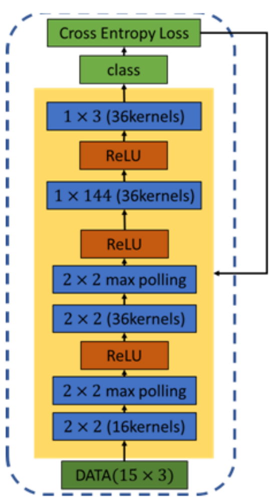


Figure 10. CNN Architecture for RSO Behavior Classification

In order to evaluate the proposed CNN approach, we have used the remaining training data to testify the model performance. Python 3 and Tensorflow are used as the simulation environment. The training of the CNN classification approach is computational expensive, but it is expected that once trained on a large dataset, the DL approach can outperform traditional classification approaches while providing a computationally efficient classification model. The overall architecture of proposed machine learning model is shown in Fig. 10.

The input data is processed in the first convolutional layer using the filter-weights. This results in 16 new datasets, one for each filter in the convolutional layer. The achieved dataset is also down-sampled so the size is decreased from 15×3 to 8×2.

These 16 smaller data are then processed in the second convolutional layer. Hence, filter-weights for each of these 16 channels are needed, along with the filter-weights for each output channel of this layer. There are 36 output channels so there are a total of 16×36 = 576 filters in the second convolutional layer. The resulting datasets are down-sampled again to size 4×1. The output of the second convolutional layer is 36 datasets of 4×1 each. These are then flattened to a single vector of length 4×1×36 = 144, which is used as the input to a fully-connected layer with 128 neurons (or elements). The final processing feeds the fully connected layer into another fully-connected layer with 3 neurons, one for each of the classes, which is used to determine the class of the RSO behaviors.

5 Numerical Results and Discussion

5.1 Training Data Generation

To generate the training data, we modified the Space Fence tracks by adding the maneuvers. Different maneuvers carry different training labels. For example, label 1 for the maneuvers to increase the orbital energy, and label 2 for the maneuvers to decrease the orbital energy, and label 3 for zero-maneuver. The steps to add maneuvers to space-track catalog data are listed as:

a. Convert the TLE to ECI at time 0.
b. Call the methods we specified in section 3 to propagate the satellites.
c. Convert the 16 waypoints back to AZ, EL, Range, Range Rate relative to a ground site.

We generated 20,000 tracks for training purpose and another 30,000 tracks for testing. The first 10,000 training tracks (with various maneuvers) are displayed in Fig. 11.

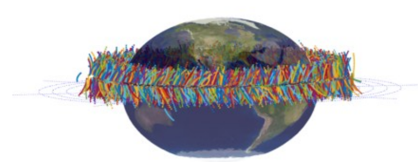


Figure 11. First 10,000 Training Tracks with Behaviors

The data format is list as:

- Each row is an observation
- Column 1: track id
- Column 2: observation id (from 1 to 15)
- Column 3: Azimuth angle (rad)
- Column 4: Elevation angle (rad)
- Column 5: Range (km)
- Column 6: Training label (from 1 to m, where m is total types of space behaviors)

5.2 Machine Learning Results and Analysis

From over 20,000 training tracks, 1/10 of the data is randomly selected as Test-Set for validating the CNN performance. The convolutional filters are initially chosen at random, so the classification is done randomly. The model performance without training can be seen in Fig. 13(a). Without training, the model cannot correctly classify the RSO behavior patterns achieving only 33.8% accuracy. The error between the predicted and true class of the input data is measured as the so-called *cross-entropy*. The optimizer then automatically propagates this error back through the CNN using the chain-rule of differentiation and updates the filter-weights so as to improve the classification error. The optimization is done iteratively thousands of times until the classification error is sufficiently low.

It is noted that the computation in TensorFlow is actually done on a batch of datasets instead of a single dataset, which makes the computation more efficient. The result is that the flowchart of TensorFlow actually has one more data-dimension when implemented in TensorFlow.

In the simulation, the batch size is set to be 128. Fig. 12 shows that as iteration increases, the training model converges nearly 100% accuracy. The results from left to right in Fig, 12 are for the case that iteration is set to be 300 and 1000 respectively. The 20,000 randomly selected dataset is used for evaluation for the well-trained CNN model.

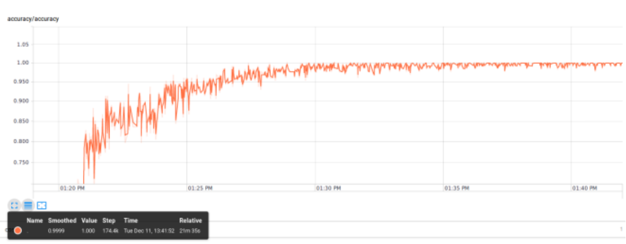
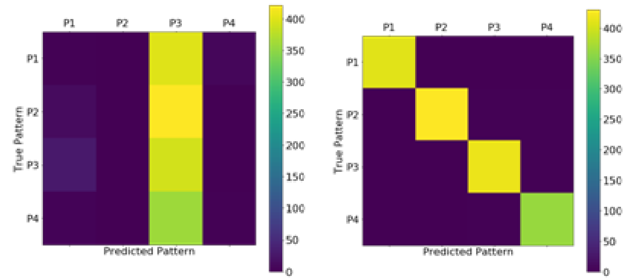


Figure 12. CNN Model Training Process

A confusion matrix [92] is utilized to determine a measure of performance [93] which supports measures of effectiveness [94, 95]. A confusion matrix supports decision-level fusion [96, 97] and can show change in performance, such as for compression [98] and fusion of images [99]. The AMIGO results can be seen through the confusion matrix shown in Fig. 13(b). The results demonstrate that the trained machine learning model can efficiently and correctly classify the RSO behaviors with 99.8% (1996/2000).



(a) (b)

Figure 13. CNN Model (a) before and (b) after Training

The classification of normal versus abnormal behaviors supports high-level fusion of situation and threat assessment [100]. Some abnormal behaviors can be the result of context changes, or movements of aerospace platforms such as space and aircraft avionics [101]. A growing concern is not only detecting the abnormal behavior, but assessing the information in conjunction with other cyber challenges from communications and navigation [102]. For example, the variations in positions could come from spoofing and false data inputs [103]. Thus, ML methods for behavior trajectory/orbital analysis provides awareness, from which the cause must be determined, whether intentional or unintentional.

6 Conclusions

In this paper, a machine learning design has been presented and implemented in AMIGO to discover space object behaviours. AMIGO models the situation as a game instead of a control problem. The game reasoning utilizes data level fusion, stochastic modelling/propagation, and RSO detection/tracking to predict the future space relations. To generate the training data, AMIGO propagates the satellite positions using maneuvering strategies using a Marko game approach, which provides a method to solve the SSA problem for unknown behaviors. The unknown behaviors exist where an elusive satellite exploits the sensing and tracking model to confuse the space sensors by corrupting their tracking estimates, while the space sensors want to decrease the tracking uncertainties. From the numerical results, it is shown that the trained machine learning model using a CNN can efficiently and correctly classify the RSO behaviors with 99.8%.

Future work would investigate the enhancements from deep learning for combined tracking, sensor management, and communications security using a multi-player game-theoretic solution in support of space situation awareness. Methods for diffusion-based cooperative space object tracking [104] and blockchain [105] are emerging methods that will be combined with the deep learning game-theoretical methods for space object behaviour classification.

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