# Learning Anomaly Detection for Generating Predictive Maintenance Models from LBS-AUV Mission Data

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## *ABSTRACT*

*Unmanned marine vehicles become most useful for security missions when they are able to operate without loss or capture for long durations without regular human intervention. Intervention can be optimized if a vehicle can intelligently predict impending failures via internal sensors such as those that already exist for the modified REMUS 600 vehicles used for LBS-AUV. A machine learning (ML) model is under development using >100 mission records each containing 10 000-100 000 time points for motor state, heading, and environmental conditions. Unsupervised ML approaches to anomaly detection shows promise for separating periods of normal/abnormal conditions. We have implemented two approaches based on deep learning and verified that they are consistent with physical correlates for expected deviations and with basic statistical methods such as an outlier threshold. For one, we examined pitch angle modelled via multivariate time series regression using a convolutional neural net. Second, we used a generative adversarial network to find anomalies in thruster response compared to goal. Validation and comparison of these models will require better annotated data from known vehicle failures.*

## 1.0 INTRODUCTION

Naval forces face the continuous challenge of optimizing Fleet maintenance needs such that operational availability is assured while costs are controlled. Maintenance strategies are now transitioning from interval-based to condition-based (CBM) to predictive and preventative maintenance (PdM). These newer approaches are enabled by high frequency data collection from embedded sensors, scientific data architecture, and machine learning models trained on this data for informing targeted maintenance actions. These actions might be determined through on-shore analysis of a long time series of data from an ensemble of vehicles executing a similar mission profile. We can also conceptualize a variety of actions to be performed by an autonomous platform running data through an on-board model, potentially retraining this model using new sensor data.

While self-repairing UxVs will require new hardware capabilities depending on the extent of the repair, we can already begin to design and lab-test algorithms that can detect known or even unknown failure modes in subsystems. At a minimum level of self-awareness, the unmanned platform should be able to abort a mission and call for assistance before a catastrophic failure. One extant example is a basic leak detector. A similar warning system should alert the operator to an increased probability of damage or out-of-envelope operations that may indicate a higher likelihood of failure on a future mission. This same principle is valid no matter where the platform falls along the spectrum of autonomy versus human dependence (DoN, 2021). Any development of PdM capabilities for any subsystem of a manned or fully autonomous system requires a sufficient amount of well-annotated data from the appropriate sensors. Fortunately, many sensors and data streams already exist for unmanned systems. Here, we use data from a specific US Navy UUV to explore the use of automatic anomaly detection algorithms based on deep neural nets (Hundman, 2018). These unsupervised algorithms require a dataset where most of the samples come from non-anomalous operations. However, validating these algorithms requires studying data with known anomalies.

## 2.0 METHODS

In this exploratory study of applying deep-learning anomaly detection to data from a UxV platform, we are using a cache of time series data from the Littoral Battlespace Sensing (LBS)-AUV, which is a modified REMUS 600 (Hydroid, Huntington Ingalls Industries). These LBS-AUV datasets were generously shared from the Naval Oceanographic Office, Stennis Space Center. We have access to 128 REMUS telemetry files ranging from 1 – 20 hours in length. Some of the shorter recordings come from calibration or test runs, while the longer recordings are from survey missions. Telemetry data includes navigation, propulsion, communications, and environmental sensors. A full analysis of this data will require in-depth annotations by the subject matter experts and vehicle operators. Based on some access to this expertise and a previously published analysis of unannotated anomalies in REMUS data (Harris, 2015), we have explored two data streams using two methodologies. First, we looked for anomalies as errors in a regression model for pitch angle using a temporal convolutional neural network (TCN) (Bai, 2018). Second, we trained a generative adversarial model for time series (TadGAN) (Geiger, 2020) on thruster RPM deviation from goal and tested on missions that seemed to have visible anomalies.

## 3.0 INSIGHTS

We found the TCN regression model for the measured pitch angle time series from telemetry is able to detect anomalous behaviour (not shown). However, the detected anomalies in pitch were highly correlated with the vehicle operating near the surface, which makes the pitch control sensitive to surface waves. Some deviations in the pitch angle are well-predicted by the velocity and fin position, which implies that a single telemetry stream may be insufficient to determine anomalous behaviour towards predicting deficiencies.

We applied the TadGAN model to the deviation between measured thruster RPM and the thruster RPM goal (Figure 1). The model was trained on a larger set of mission data that appeared to be more normal, with much smaller normalized deviations. Anomaly predictions from the TadGAN show that not all deviations are classified as anomalies. The putative anomalies seem to have a combination of irregular shape and large amplitude of deviation.

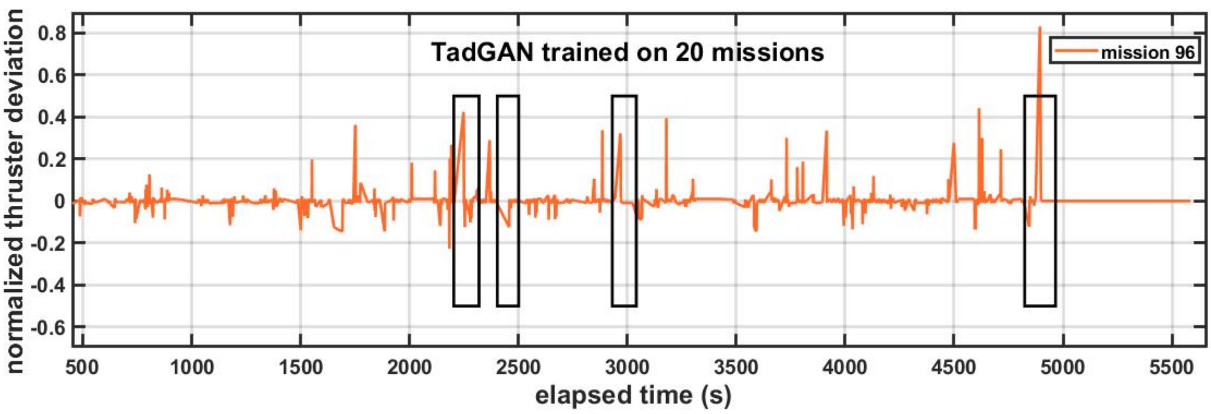


**Figure 1: Generative adversarial network anomaly detections (black boxes) for LBS-AUV thruster RPM deviation from goal, following training on twenty (20) similar missions [5].**

## 4.0 CONCLUSION

This exploratory analysis of LBS-AUV data will require significant future effort to determine the functional relevance of the anomalies detected by the deep learning algorithms. Our dataset is biased towards successful missions and operational vehicles. Many datasets related to maintenance are fundamentally biased in this way – rarely would a vehicle be run into a significant failure mode, more likely a maintenance event would be planned to repair and replace components based on an "oil change" type of manufacturer's recommendation. Further work will require detailed input from subject matter experts and design of an experiment, or careful data selection, that contains anomalies correlated with mission-relevant deficiencies.

## REFERENCES

[1] Department of the Navy Unmanned Campaign Framework, March 16th 2021

[2] Hundman, K. et al. (2018) "Detecting Spacecraft Anomalies Using LSTMs and Nonparametric Dynamic Thresholding," in KDD '18: The 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, August 19-23, London, United Kingdom. ACM, New York, NY, USA

[3] Harris, W.R. (2015), "Anomaly Detection Methods for Unmanned Underwater Vehicle Performance Data," Masters Thesis, Massachusetts Institute of Technology

[4] Bai, S. et al. (2018) "An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling," arXiv:1803.01271v2 [cs.LG] 19 Apr 2018

[5] Geiger, A. et al. (2020), "TadGAN: Time Series Anomaly Detection Using Generative Adversarial Networks," arXiv:2009.007769v3 [cs.LG] 14 Nov 2020, IEEE Big Data 2020