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Exploring the Mahalanobis-Taguchi Approach to Extract Vehicle Prognostics and Diagnostics

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Abstract

Army logistical systems and databases contain massive amounts of data that require effective methods of extracting actionable information and generating knowledge. Vehicle diagnostics and prognostics can be challenging to analyze from the Command and Control (C2) perspective, making management of the fleet difficult within existing systems. Databases do not contain root causes or the case-based analyses needed to diagnose or predict breakdowns. 21st Century Systems, Inc. previously introduced the Agent-Enabled Logistics Enterprise Intelligence System (AELEIS) to assist logistics analysts with assessing the availability and prognostics of assets in the logistics pipeline. One component being developed within AELEIS is incorporation of the Mahalanobis-Taguchi System (MTS) to assist with identification of impending fault conditions along with fault identification. This paper presents an analysis into the application of MTS within data representing a known vehicular fault, showing how construction of the Mahalanobis Space using competing methodologies can lead to reduced false positives while still capturing true positive fault conditions. These results are then discussed within the larger scope of AELEIS and the resulting C2 benefits.

Introduction

During Operation Iraqi Freedom, Soldiers of the 56th Infantry Brigade Combat Team providing escort to a fuel convoy found themselves in the middle of the Iraqi desert waiting for recovery vehicles to arrive [1]. While self-recovery efforts had overcome previous situations during this mission, a broken-down truck eventually halted the convoy and placed friendly forces at risk. As one soldier pointed out “Whenever we can't self recover, we wait for additional assets to get to us. Sometimes that wait is only a couple of hours and sometimes it is longer.” Fortunately, all ended well and the fuel was delivered safely. However, this incident illustrates the challenge and ramifications of in theater fleet asset management.

The Army is working toward modernizing its fleet logistics [2]–[4], yet the goal of an effective decision support system (DSS) remains elusive. While much logistics data exists in dedicated databases, there are limitations to providing proactive maintenance type information to avoid breakdowns. Efficient combat support and combat service support demands look-ahead for fleet management for future manned and unmanned vehicles. The multitude of databases each has their own specific function and never provides a full picture for the fleet managers, operators, and commanders to utilize. Furthermore, these databases do not do an adequate job of identifying failure modes or case-based, root-cause analysis.

New tools are needed that provide up-to-date information mined from the available data on the vehicle fleet to find potential problems. An effective Enterprise Intelligence System will find data from as many sources as possible, process in an integrated fashion, and disseminate information products on the readiness of the fleet vehicles. Doing so, we may be able to avoid such scenarios as waiting for recovery vehicles in a combat zone. Making sure vehicles stay operational is a combination of predictive health maintenance (condition based maintenance plus root cause analysis) and parts supply availability. Agent-Enabled Logistics Enterprise Intelligence System (AELEIS) is being developed as a tool to assist logistics analysts with assessing the availability and prognostics of assets in the logistics pipeline with data from multiple, heterogeneous sources. Data is aggregated and mined for data trends, and reasoning and prognostics tools evaluate the data for relevance and potential issues.

Within AELEIS, we are developing a comprehensive failure mode diagnosis and health condition assessment technique for vehicle health by employing the Mahalanobis-Taguchi System (MTS) based multi-parameter, multi-input pattern recognition methodology. The MTS analysis provides a real-time, continuous monitoring system that will take vehicle history data and translate it into a probability of failure. Data acquired on vehicle history and maintenance repair will be mined and added to a database and used within the probability of failure calculations and revalidation to create a learning system. The MTS methodology is selected due to its reported accuracy in forecasting trends observed in correlated data sets without intensive computations (thus lower cost) [5].

This paper chronicles some of the challenges experienced attempting to extend the MTS approach to the available data as well as initial results from modifying MTS to these vehicular data sets. We believe our approach takes a more holistic view than the initial strategy, accounting for the impact on false negatives as well as false positives within the resulting analyses. By examining the impact of applying MTS in the development stages, more meaningful and better understanding of results can be achieved. This paper briefly overviews the AELEIS concept showing where MTS fits and why it was selected over alternative approaches. A more detailed discussion of MTS is presented, followed by application within the vehicle logistics domain. We wrap up with a brief summary and key lessons learned.

AELEIS Concepts

Figure 1 shows a conceptual view of the AELEIS decision tool. Using a Service Oriented Architecture (SOA), AELEIS data extraction agents connect to the various databases and other data sources. The extraction agents scan the databases for key pieces of data and then publish that data back to the AELEIS Central Core. There, the reasoning agents determine what tools are needed based on data clustering. The mining and trending agents find the information in the data (they may also instruct the extraction agents on further data to find). Finally, compiled actionable information is published in a standard format out to users. This information is then picked up by a decision tool allowing the user to see the information, drill-down to see where the information originated, and make an informed decision on the logistics plan.

Our research into causal data mining looked into Support Vector Machines (SVM) and radial basis function neural networks. Both of these methods are kernel based approaches, however, they are self organizing during training. The problem that we encounter with this type of method is that the results become ambiguous. Our challenge was that we would have to generate much more data than what we currently had in order to adequately train these algorithms. We needed an algorithm that would provide clear results with much less data. Our research efforts lead us to the Mahalanobis-Taguchi System. MTS provided us with the clear diagnostics capability we were looking for, while needing much less data. Our initial results showed that the MTS algorithm is able to perform the diagnostics task with representative data. We used this as a starting point to more fully develop the MTS algorithm. In future work we plan on expanding how MTS can also find causal relationships in the data.

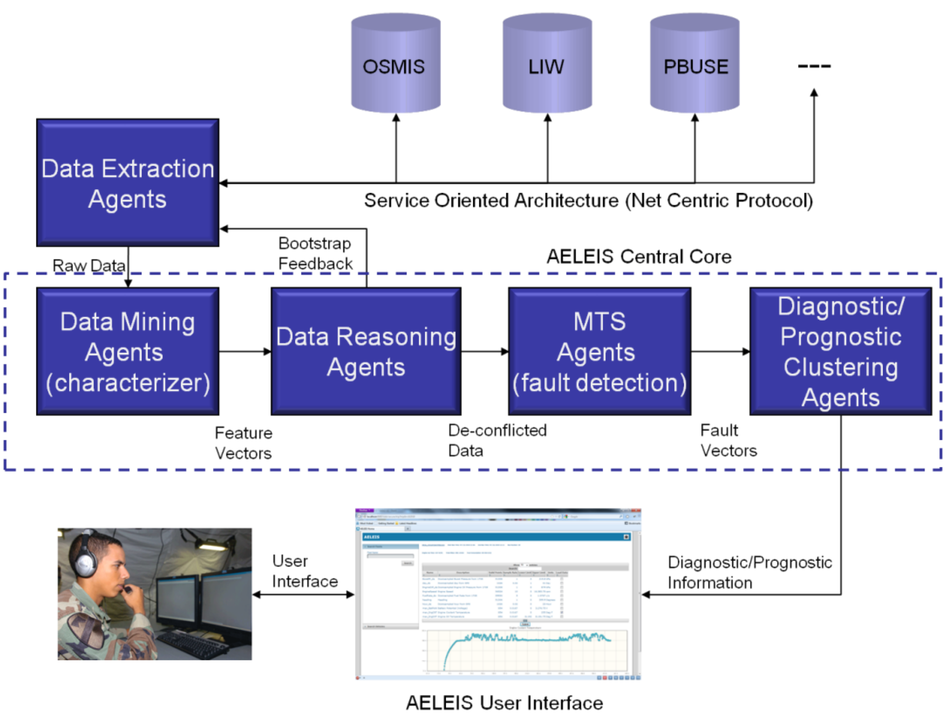

Figure 1: Conceptual view of the AELEIS decision tool.

Preliminary AELEIS development relied on simulated data which was constructed to emulate degradation of performance for three fault modes over time. We have since been able to obtain a variety of government-furnished data which we have used to more fully develop AELEIS (and the MTS approach) as outlined here.

Mahalanobis Distance

Mahalanobis Distance (MD) is a distance measure derived from an analysis of the deviation in the mean values of different variables in multivariate analysis considering the correlation between the variables. As a discriminant analysis method, MD is useful in determining the similarity of a set of values from an unknown sample to a set of values measured from a collection of known samples. MD proves to be superior to other multidimensional distance measures due to the following [6]:

- Correlation between the variables is used in its calculation.
- It is very sensitive to inter-variable changes in the reference data.
- It is not affected by the dimensionality of the dataset.

Assuming the dataset consists of k variables; *i* is the variable (i = 1, 2, …, k); n represents the number of samples in the dataset; and j is the sample number (j = 1, 2, …, n), the variables are standardized as defined in Equation (1).

$$z_{ij} = (x_{ij} - m_i)/s_i \tag{1}$$

m_i and s_i represent the mean and standard deviation of the *i*th variable, respectively; and z_{ij} is the standardized vector obtained from the standardized values of x_{ij}. MD values are calculated as defined in Equation (2).

$$MD_j = \frac{1}{k}\boldsymbol{Z'}_{ij}\boldsymbol{C}^{-1}\boldsymbol{Z}_{ij} \tag{2}$$

MD_j is the Mahalanobis distance calculated for the *j*th case and $\mathbf{C}^{-1}$ represents the inverse of the correlation matrix of the variables in the dataset.

Mahalanobis Taguchi System

Genichi Taguchi applied a robust engineering methodology using Mahalanobis distances to develop the Mahalanobis-Taguchi Strategy (MTS) as a diagnosis and forecasting method for multivariate data. It is a pattern recognition technology that assists in quantitative decision-making by constructing a multivariate measurement scale using data analytic procedures with the MD values [6], [7]. MTS can be used to develop a scale to measure the degree of abnormality of data measurements compared to a calculated “normal”.

Within MTS, initial Mahalanobis distances are calculated, then orthogonal arrays (OA) and signal-to-noise (S/N) ratio are used to identify attributes of importance. Attributes adding only noise and not signal are removed from the process, validating against known abnormal conditions. In developing a multivariate measurement scale it is important to (1) have a reference point to the scale, (2) validate the scale, (3) select the important variables adequate for measuring abnormality, and (4) be able to carry out future diagnosis with the measurement scale. These form the basis of MTS application with the steps formalized in Figure 2.

The Mahalanobis-Taguchi System (MTS) was identified to work the diagnostics/prognostics challenge. MTS can be used for fault detection, isolation, and prognostics [7]–[9]. Previously, we’ve had MTS fuse data from multiple sensors into a single system level performance metric using Mahalanobis Distance (MD) and generate fault clusters based on MD values. MD thresholds derived from clustering analysis were used for fault detection and isolation. Figure 3 (a) shows a conceptual view whereby the MD (magnitude and angle) can help detect that a fault is occurring and which type of fault. Figure 3 (b) shows the same concept with a compound

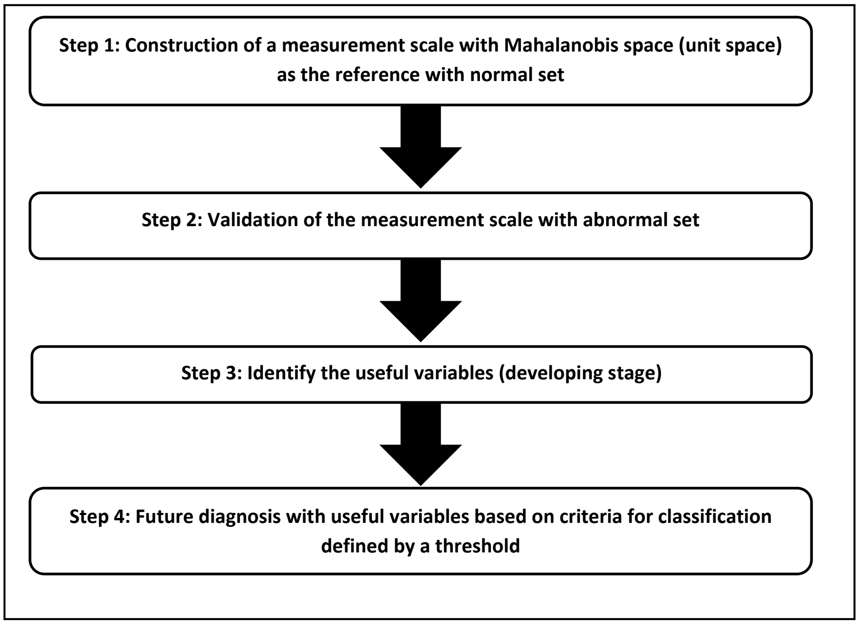

Figure 2: MTS process as outlined by Taguchi

fault. In this case, either Fault 1 or Fault 2 may be indicated by the MD. In particular, a change in parameters would be needed to properly identify the fault. By creating a self-learning scheme, the proper faults can be identified, and, more importantly, which parameters to use to separate the faults. The manner in which we have developed the initial simulated AELEIS data, we were most likely to see the compound fault situation occur in the Fuel Injector vs. Fuel Filter fault conditions.

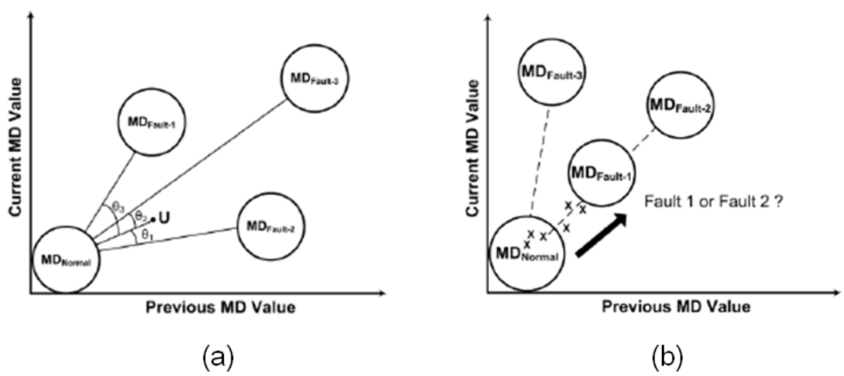

Figure 3: Mahalanobis-Taguchi System (MTS) where the Mahalanobis distance around a fault cluster determines the variance from normal (lower left corner) for simple fault conditions (a) and compound fault conditions (b).

Figure 4 shows an example of a compound fault that is indistinguishable using only outlet pressure on a pump [10]. The MTS method holds the most promise for the classification of root cause fault analysis. The main drawback to the MTS method is that the possible root causes must be known *a priori*. Primarily, this is due to the training and placement of the cluster location within the Mahalanobis space. Other methods that we have looked into for root cause analysis include Support Vector Machines (SVM) and radial basis function neural networks. Both of these methods are kernel based approaches, however, they are self organizing during training. The problem that we encounter with this type of method is that the results become ambiguous, where as the results of MTS are easily understood as to what the root cause is and even allows for predictive analysis.

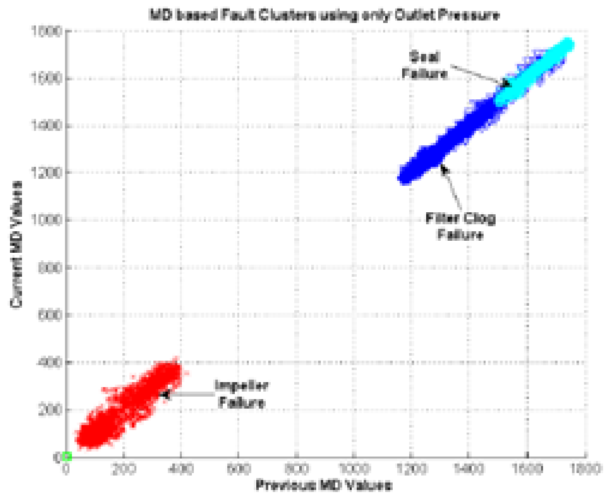

Figure 4: Example MD based fault clusters using only the outlet pressure for a pump [10]**.**

Applying the MTS Approach

Concurrent with AELEIS development, the Army Tank-Automotive Research Development & Engineering Center (TARDEC) has been investigating the opportunities of capturing individually identifiable data from fleet vehicles for health and maintenance capabilities. Portions of this data have been made available for research within AELEIS, specifically the detection and prediction capabilities offered through MTS. Due to the nature of the data, certain details cannot be provided. However, general details are provided along with results.

There were two primary data sets available for testing and development we'll label as pre- and post-launch. The pre-launch data was collected over a longer time period (roughly 3 years) and consisted of a smaller number of vehicles (around 10). Data formatting was fairly uniform across the entire data space with the same 51 attributes available for each collection, but collected at different frequencies. Data collections were performed for each vehicle "run" which could consist of a few minutes to many hours. The post-launch data had been collected over approximately one year with a much larger breadth of vehicles (hundreds). Data formatting was often not consistent across vehicles (which could be different types) and could be inconsistent within a vehicles' files (for example, different attribute orderings or invalid data when sensors were not operational or installed, etc.). Attributes for the post-launch vehicles typically ranged from 120-150 per vehicle.

Fault conditions are key to implementing the MTS approach as they drive the selection of variables used in the final MD calculations. The pre-launch vehicles had one identified fault condition provided. This fault was the first initially explored and is the one which will be addressed further here. The post-launch vehicles had over 100 documented fault (or potential fault) cases—two of which were examined following the pre-launch examination. These initial MTS efforts helped hone the process of applying a modified Mahalanobis Taguchi approach on what we will call the pre-launch vehicle's fault F.

Previous TARDEC analysis had identified differences in the data from a run prior and following the fixing of fault F. This analysis referenced a data set recorded approximately 6 runs prior, and another set approximately 6 runs following the fix. The initial MTS analysis focused on these two runs, attempting to best compare ‘apples to apples’ with the existing analysis. For this initial look, the most relevant subset of fields was selected which all were collected at the same sampling rate. These 6 fields were analyzed, one was used to divide the data (following the TARDEC analysis criteria) and another was removed due to the S/N ratio, leaving 4 factors. These initial 4 factors were successful in discriminating the normal and test cases of fault F as shown in Figure 5. However, applying the Mahalanobis Space to other runs both prior and following the fix did not provide as much consistency as desired.

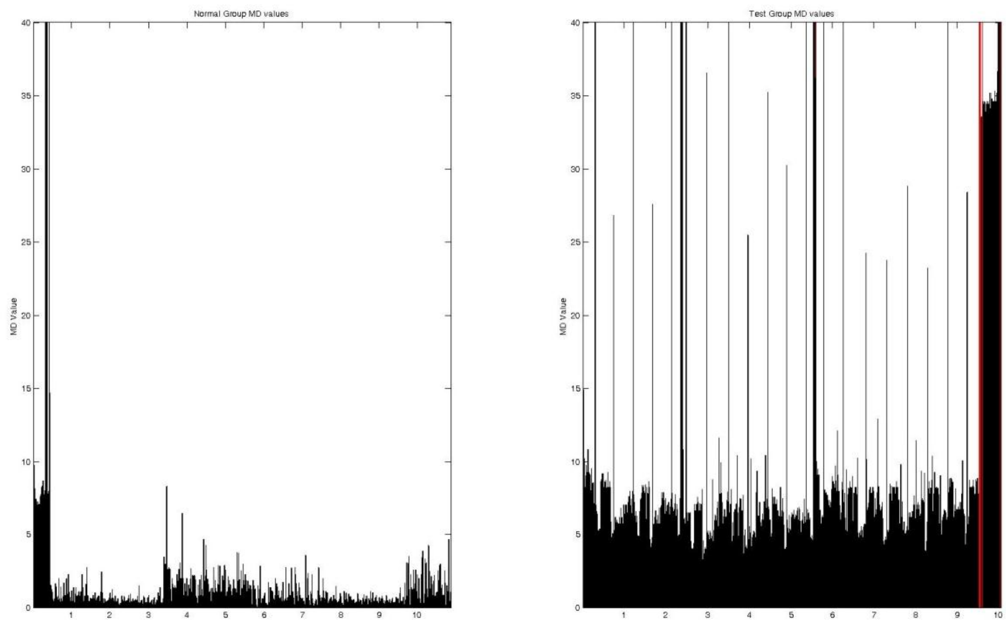

Figure 5: MD values from the normal (left) and abnormal (right) data with initial 4-factors

The post-launch data simplified some of the pre-launch challenges in that there were numerous faults and the data was all collected at the same fidelity, eliminating the need for re-sampling. Two instances of a similar fault were examined starting from a much richer set of attributes than the original fault F scope. This post-launch examination took 30 variables and iteratively reduced them down to 6. Within this analysis, the removal of outliers was introduced for construction of the Mahalanobis Spaces.

Traditionally, the entire normal group is utilized to construct the unit space as step 1 in MTS. However, with the amount and variability of data (due to vehicles, sensors, etc.) the resulting Mahalanobis Space (MS) from the vehicular data isn’t necessarily as clean as in existing work. Therefore, we sought mechanisms to remove outliers from consideration of the initial MS construction. Removing outliers constructs a “narrower” space which leads to better detection of abnormal conditions (increasing true negatives & decreasing false negatives) at the expense of flagging some of the removed normal data as abnormal (false positives). This analysis showed that the S/N ratio profiles were apt to change as more aggressive thresholds were implemented. The result was increased understanding of the ramifications of variable inclusion/exclusion within the scope of false negative and false positive detection. These initial investigations have resulted in revisiting fault F and the following analysis of what variables seem most appropriate from the entire perspective.

To simplify the scope of examination, pre-launch data was normalized to the same frequency as the post-launch data. This required both up-sampling and down-sampling of the data, depending on attribute. Some of the fields may have not had enough variance (e.g., if the standard deviation was 0, the resultant correlation matrix would be singular and no inverse could be obtained) and others, such as the day of the week, were irrelevant or redundant. The preliminary work took the 51 variables down to 16. In addition, the normal data was constructed from the entire 6 runs following the fix, and a test data set was constructed from the 6 runs prior to the fix. The single-run test data was also retained and used within analyses.

From the established variable set, the initial MTS data analysis step was performed, comparing the constructed MS against the abnormal data. Figure 6 shows the result utilizing the entire 6-run dataset for the abnormal condition. There is a noticeable distinction in MD values between the normal and abnormal groups (as seen in the top two charts), and all variables appear to add more noise than signal (larger S/N ratios are better, thus, smaller negative S/N ratios are better).

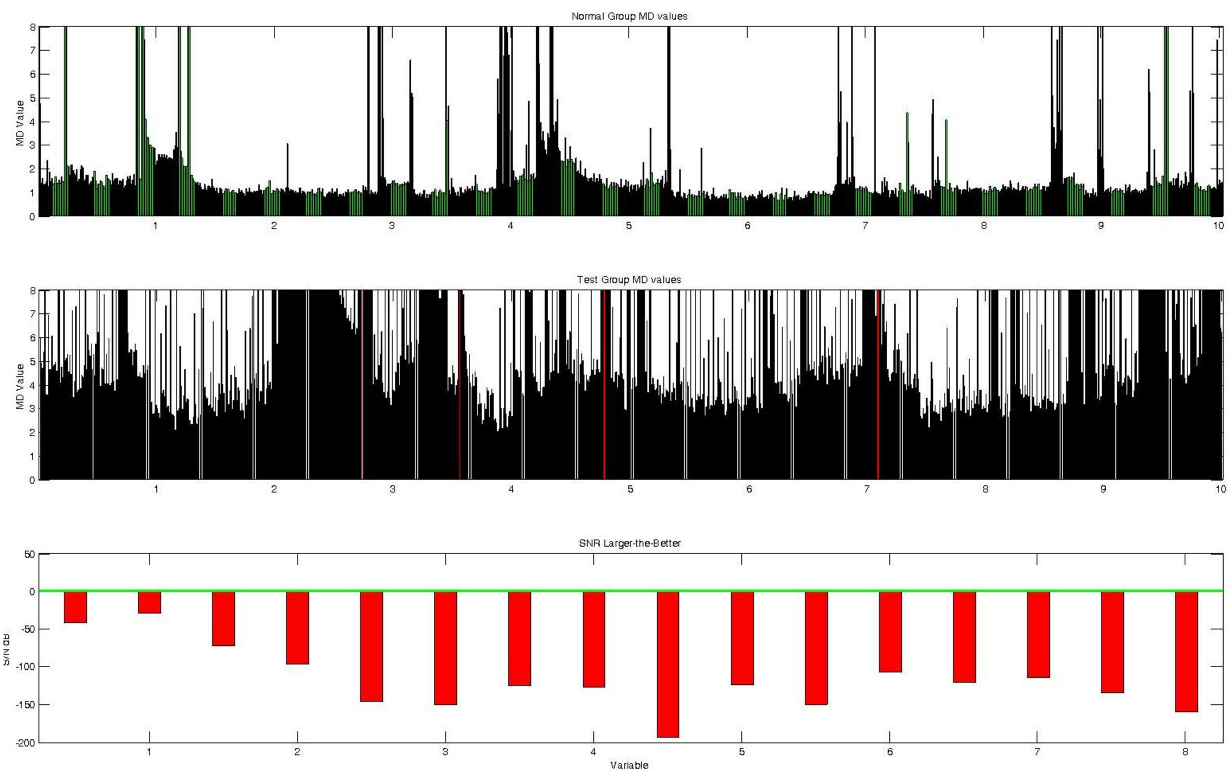

Figure 6: Fault F 16 variable MS showing MD values from the normal group (top), full abnormal group (middle) and the S/N ratio dB values (bottom)

This MS was also compared against the single abnormal run as previously tested (and selected to align with TARDEC's independent analysis). Figure 7 shows the same MS constructed against the single test file. In this case, notice there are two variables with a positive S/N ratio. This indicates that these two variables are most useful in characterizing these abnormal values as abnormal. In other words, it is a measure of the effectiveness in discrimination capabilities of each variable. Using this S/N ratio information in isolation might have caused inclusion of these variables within the refinement of the Mahalanobis Space. However, consulting Figure 6 will show this to be a bad idea. Notice the single-file fault space is favoring variables 6 and 7 (slightly positive and slightly negative, respectively). Comparing to the S/N ratios over the larger fault space we wish to detect (Figure 6) shows that these two variables do not add nearly as much signal across the other files where the vehicle is operating within the fault condition.

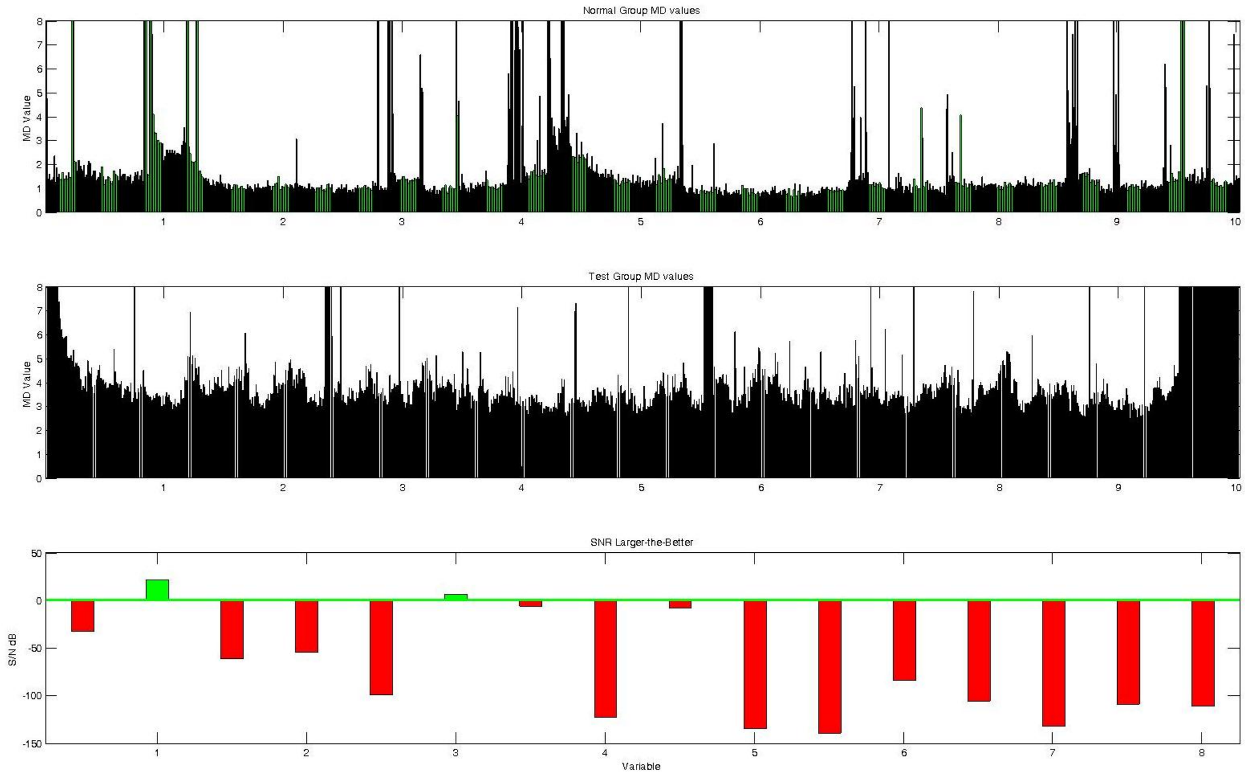

Figure 7: Fault F 16 variable MS showing MD values from the normal group (top), single abnormal file (middle) and the S/N ratio dB values (bottom)

This first analysis shows why the initial work effort on fault F may have been flawed by being too narrow in scope. MTS does fairly well at discerning normal from abnormal – but with the stochastic nature of vehicle use, we may desire to build in more generality to account for the "instability" of the normal data. In addition to considering the larger data sets, the multiple threshold investigation was applied to fault F. It was mentioned above, the more outlier removal which is performed prior to construction of the MS, the better detection achieved. However, the caveat is increased discrimination in detecting the abnormal data also increases the false positive detection within the removed normal data. This is often at the extreme cases within the threshold-removal process. For instance, Figure 8 shows the Mahalanobis Distance values for the normal data against the Mahalanobis Spaces constructed with MD thresholds of 2 and 1.5.

To understand the threshold process begins with understanding the Mahalanobis Space. The statistical nature of MDs produces a unit Mahalanobis Space from the normal data. This means the average MD value across the normal data will be 1. The validation of the MS is essentially ensuring the MD values of the abnormal set are significantly distinguishable from the normal MD values. For automating the outlier removal process, an intermediate program was constructed to iteratively filter out any data instances where the MD value was above the threshold value. This could take in any initial "normal" group and tune it down to remove outliers from construction of the MS. The higher the threshold, the fewer data removed. The lower the threshold, the more data removed and the higher the chance for reducing false negatives and increasing false positives.

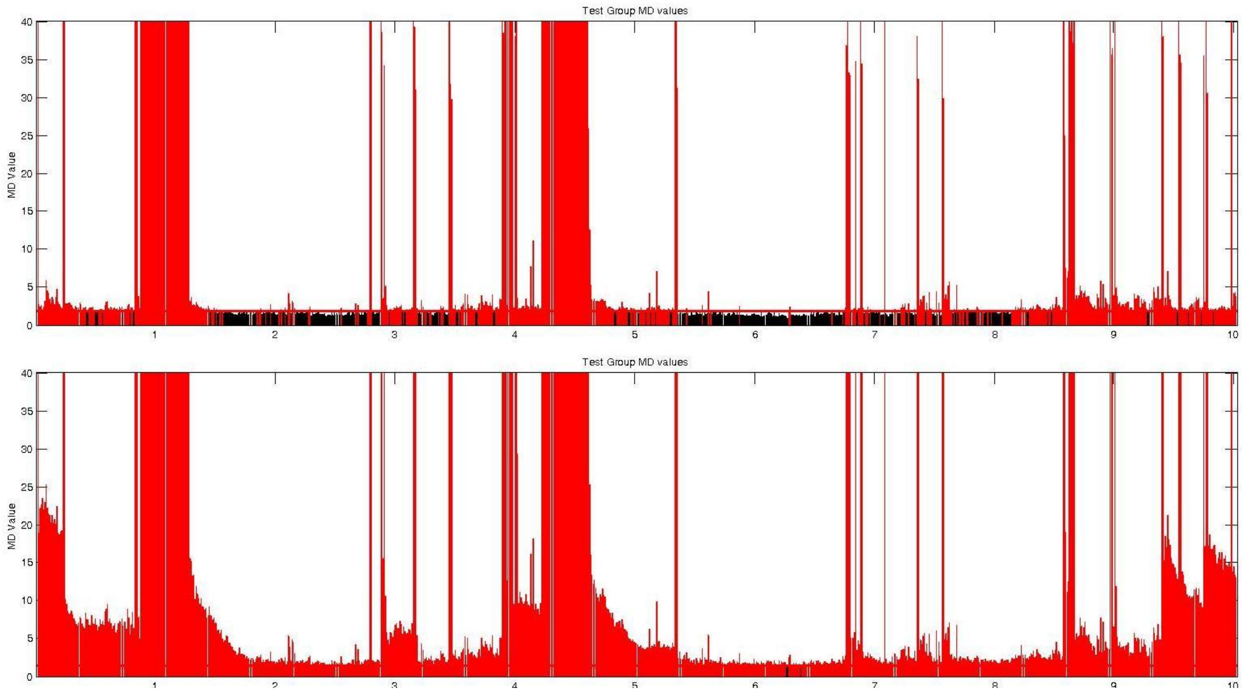

Figure 8: Fault F 16 variable MS plotting the entire Normal group's MDs calculated from Mahalanobis Spaces constructed using a threshold at 2 (above) and 1.5 (below)

Again, Figure 8 shows graphically the potential increase in false positives with markedly increased MD values when using the 1.5 threshold group to create the Mahalanobis Space. However, even the threshold at 2 shows at least two major areas prone to false positives. Table 1 shows the threshold MD values along with the percentage of data removed with that threshold.

Table 1: Thresholds and data removed from MS construction

Threshold MD Value	Normal Data Removed From MS Construction
10	0.72%
9	0.76%
8	0.81%
7	0.94%
6	1.11%
5	1.43%
4	1.91%
3	12.1%
2	15.4%
1.5	54.6%

It is not surprising to see that such an increase in removal between thresholds of 2 and 1.5 results in such an increase in MD values in the resulting Mahalanobis Space. Additionally, consulting the same plots for thresholds of 6, 5, and 4 shows the tipping point of introducing additional false positives as shown in Figure 9.

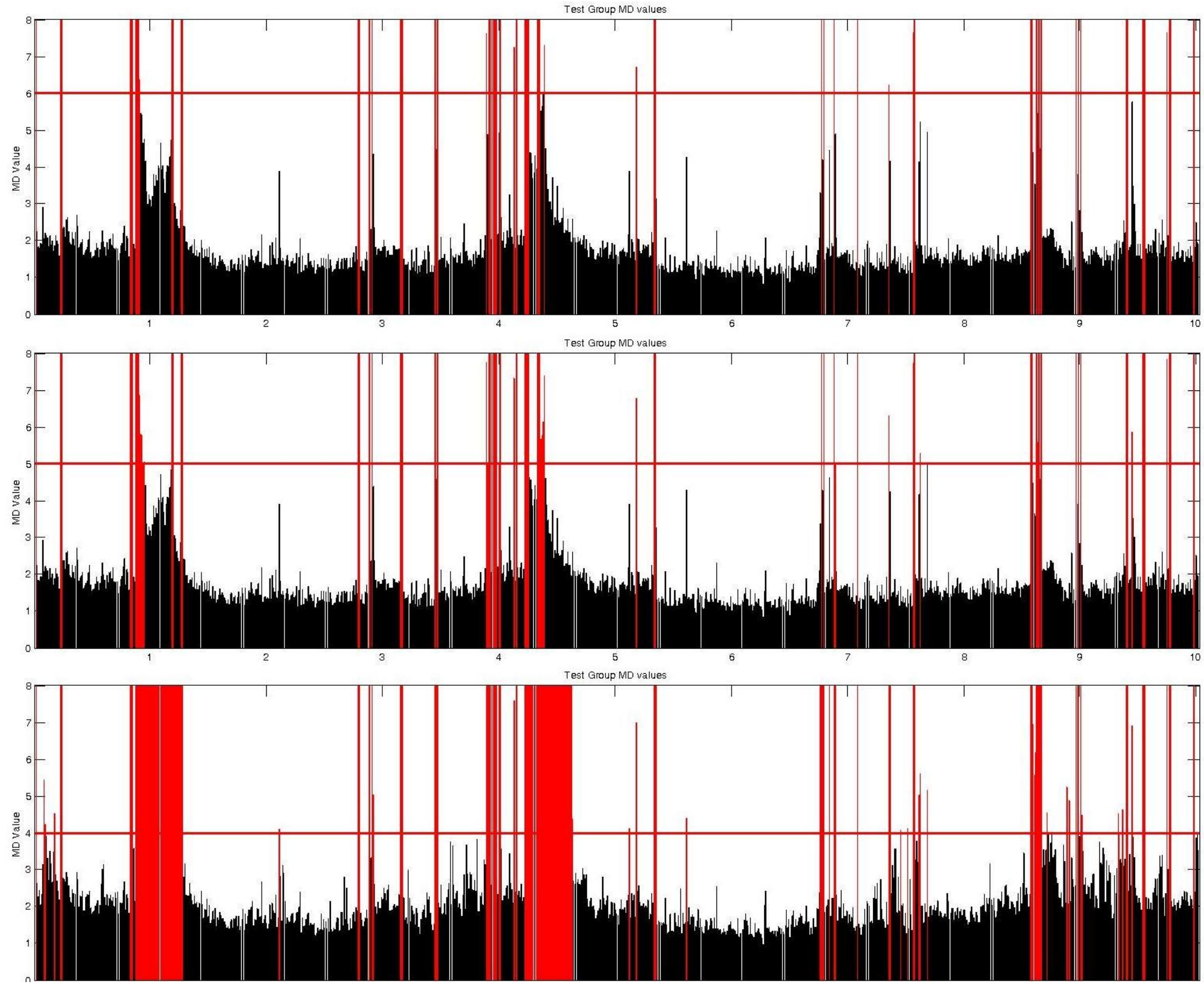

Figure 9: Fault F 16 variable MS plotting the entire Normal group's MDs calculated from Mahalanobis Spaces constructed using a threshold at 6 (above), 5 (middle) and 4 (below)

In addition to observing the impact on potential false positives, the S/N ratios were analyzed using the threshold-created spaces against the targeted test data (complete set). As the thresholds increased, the MS data changed and therefore the S/N profiles changed as well. This was used to determine trends, indicating which variables may be becoming more or less useful in identifying the abnormal data. Examples of the 16-variable data with the same thresholds of 6, 5, and 4 are shown as Figure 10, Figure 11, and Figure 12.

From this analysis, the highest noise (lowest S/N ratio) variables were removed, leaving any variables which seemed might be useful even though the S/N ratio was still negative. The result was a reduction from 16 variables to 10 variables. The initial impression was an entire set of 8 variables exhibiting similar characteristics would be ripe for removal. Interestingly, following the threshold-investigating, two seemed to hold enough potential to remain in additional analyses.

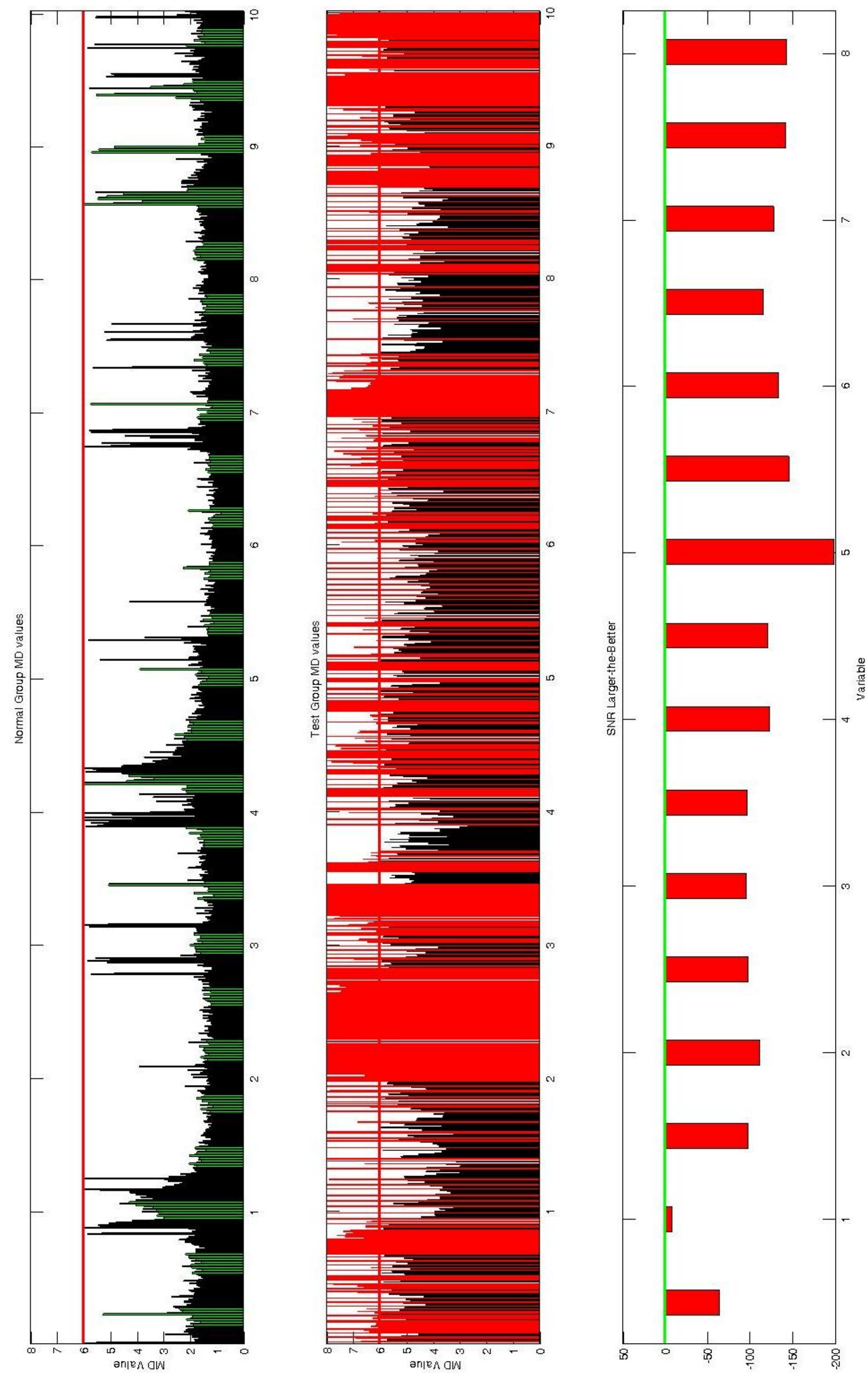

Figure 10: Normal MD values, Test MD values, and S/N dB ratio from MS with threshold at 6

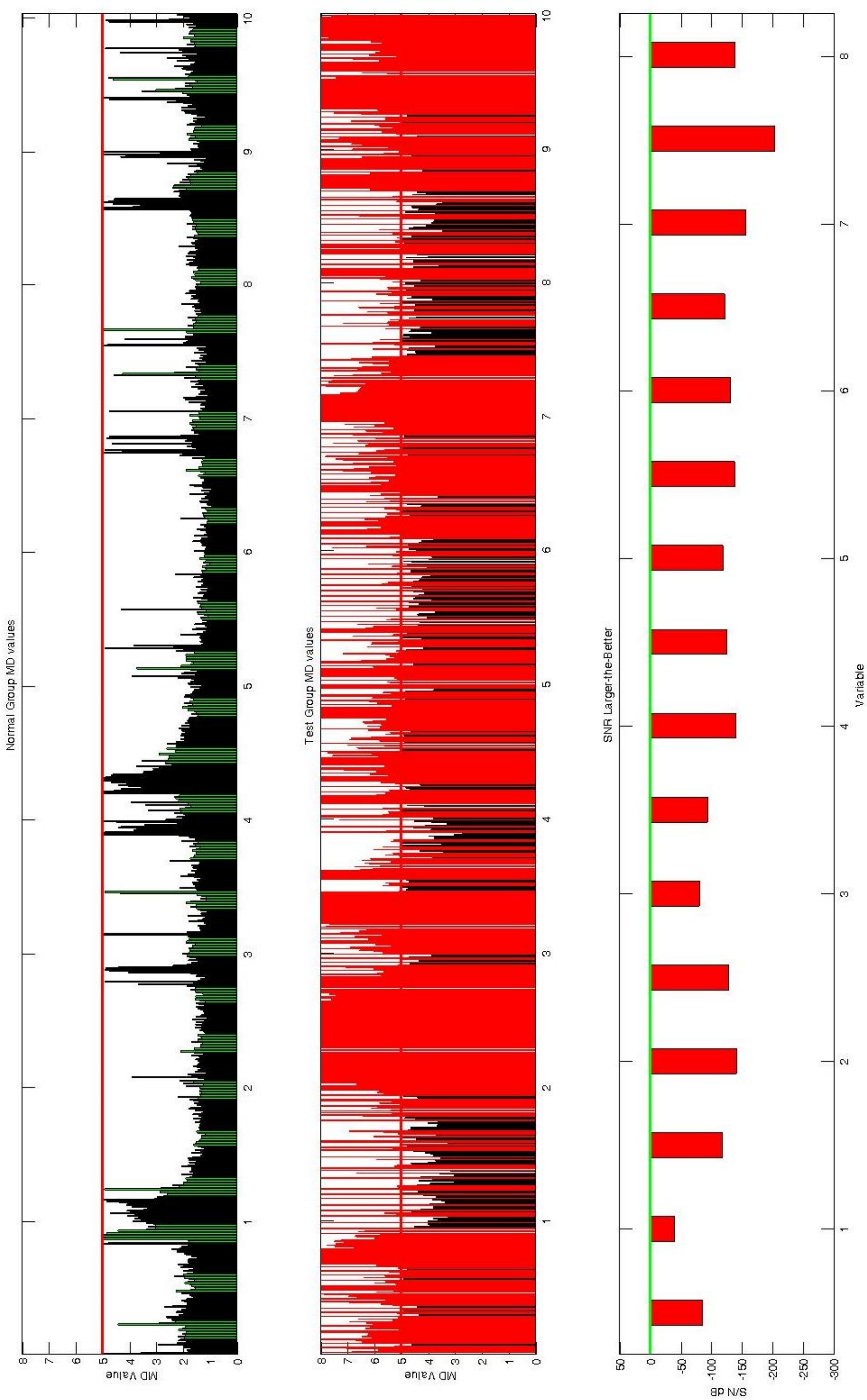

Figure 11: Normal MD values, Test MD values, and S/N dB ratio from MS with threshold at 5

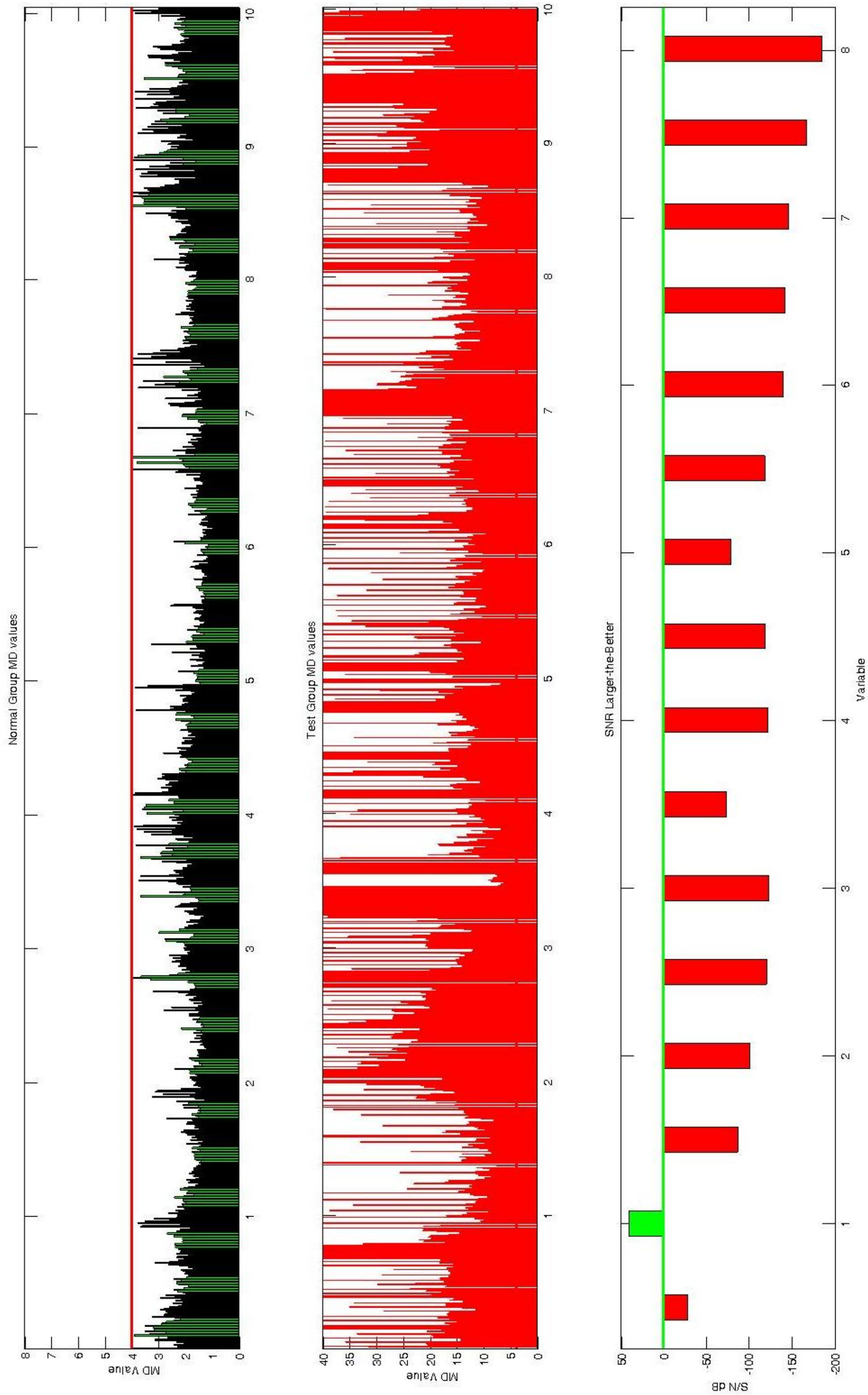

Figure 12: Normal MD values, Test MD values, and S/N dB ratio from MS with threshold at 4

From the 10-variable data, the same threshold analysis was applied comparing the S/N profiles for the resultant (entire, original) norm and (complete) test groups across Mahalanobis Spaces constructed from various thresholds. Table 2 shows the equivalent data removal within this space, following similar trends to the 16-variable analysis.

Table 2: Thresholds and data removed from MS construction of the 10-variable set

Threshold MD Value	Normal Data Removed From MS Construction
10	0.64%
9	0.73%
8	0.86%
7	1.13%
6	2.23%
5	11.9%
4	12.0%
3	12.6%
2	28.1%

The 10 variables were again reduced down to the most significant 7 and analyzed with the threshold approach. The removal results are overviewed in Table 3

Table 3: Thresholds and data removed from MS construction of the 7-variable set

Threshold MD Value	Normal Data Removed From MS Construction
10	0.76%
9	0.89%
8	1.16%
7	11.4%
6	11.5%
5	11.5%
4	11.9%
3	14.8%
2	33.6%

Lessons Learned

The current analysis of fault F appears to indicate that we should be able to achieve good detection with reduced false positives with either the 16 variable or 7 variable sets. These two configurations are shown in Figure 13 and Figure 14, respectively. It appears perhaps the robustness of detection comes in the spreading of the S/N ratios across a wide breadth of variables as opposed to the traditional approach focusing heavily on variable reduction.

One of the problems hinted at with the post-launch vehicle data is the same variables are not always available across vehicles. This complicates applying the MTS process as missing variables are not traditionally encountered within MTS. If a method can be implemented for handling missing data, having a larger set of attributes to draw on for the MD values may be of additional benefit. Continuing research will explore the tradeoffs with reducing the variable set versus increasing the robustness of the fault detection balancing the reduction of false negatives with the increase of false positives.

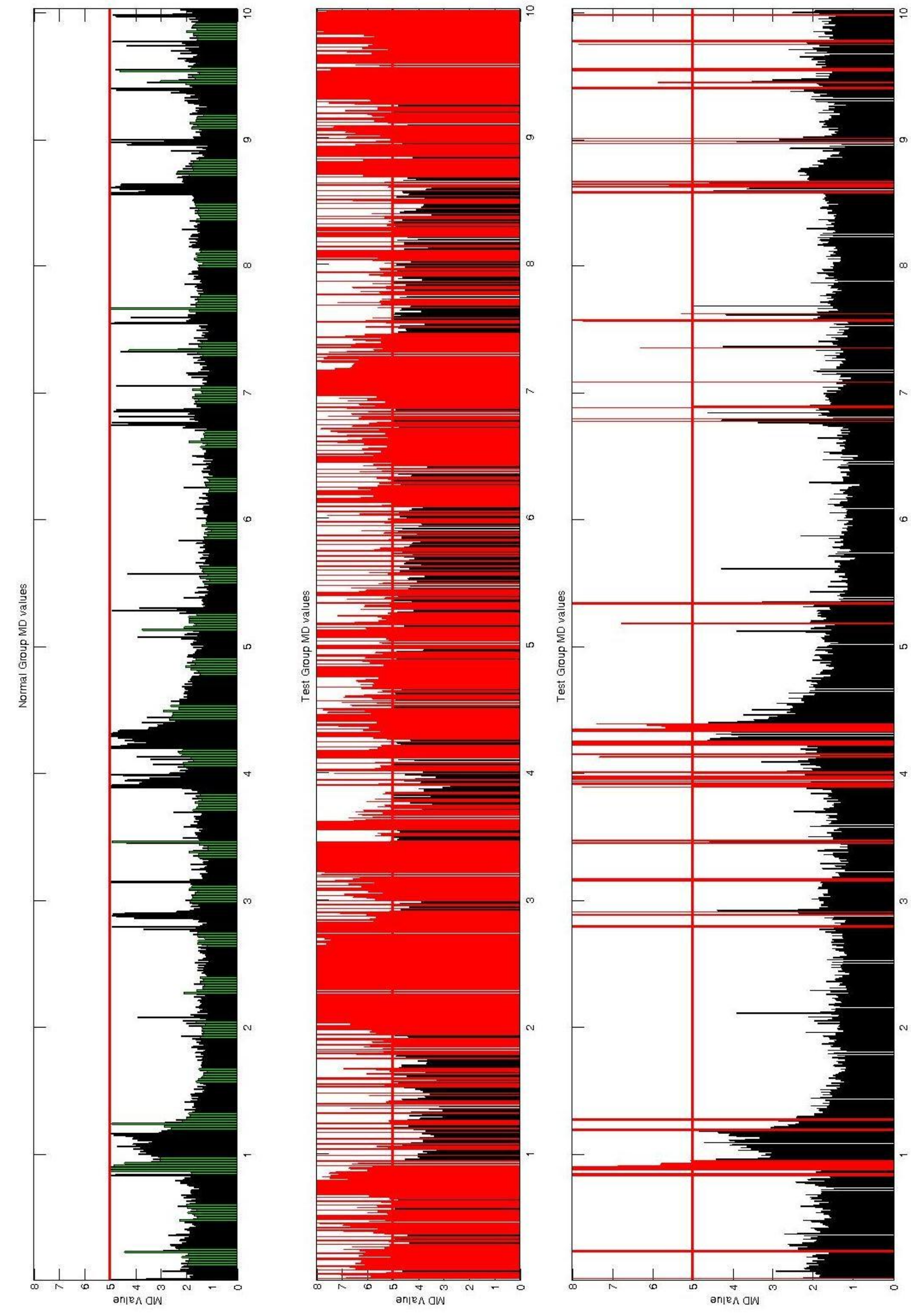

Figure 13: 16 Variable MS Threshold 5, MD values of the threshold space, full test space, and full normal space

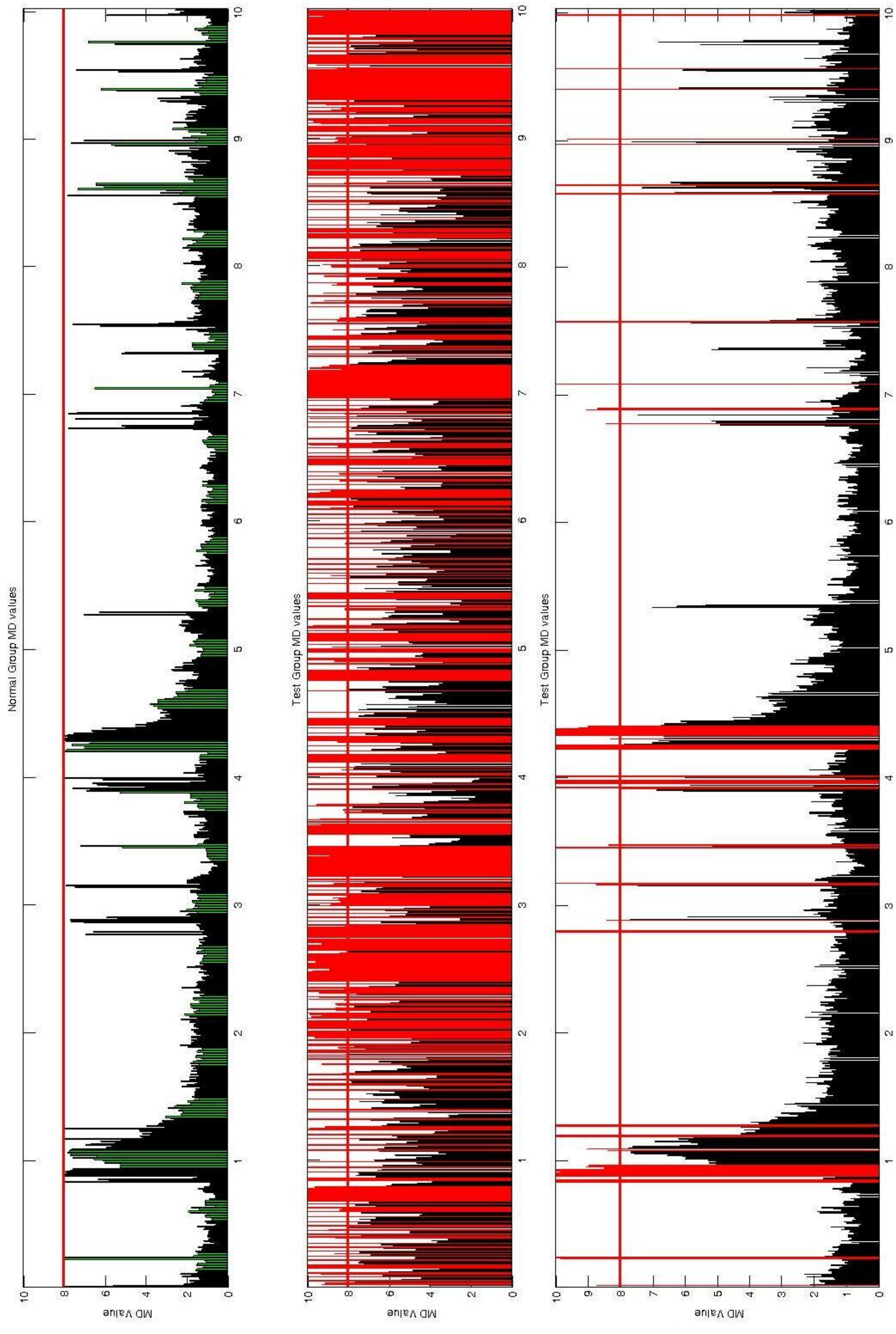

Figure 14: 7 Variable MS Threshold 8, MD values of the threshold space, full test space, and full normal space

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