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Space Telemetry Anomaly Detection Based on Statistical PCA Algorithm

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***Abstract*—**The critical concern of satellite operations is to ensure the health and safety of satellites. The worst case in this perspective is probably the loss of a mission, but the more common interruption of satellite functionality can result in compromised mission objectives. All the data acquiring from the spacecraft are known as Telemetry (TM), which contains the wealth information related to the health of all its subsystems. Each single item of information is contained in a telemetry parameter, which represents a time-variant property (i.e. a status or a measurement) to be checked. As a consequence, there is a continuous improvement of TM monitoring systems to reduce the time required to respond to changes in a satellite's state of health. A fast conception of the current state of the satellite is thus very important to respond to occurring failures. Statistical multivariate latent techniques are one of the vital learning tools that are used to tackle the problem above coherently. Information extraction from such rich data sources using advanced statistical methodologies is a challenging task due to the massive volume of data. To solve this problem, in this paper, we present a proposed unsupervised learning algorithm based on Principle Component Analysis (PCA) technique. The algorithm is particularly applied on an actual remote sensing spacecraft. Data from the Attitude Determination and Control System (ADCS) was acquired under two operation conditions: normal and faulty states. The models were built and tested under these conditions, and the results show that the algorithm could successfully differentiate between these operations conditions. Furthermore, the algorithm provides competent information in prediction as well as adding more insight and physical interpretation to the ADCS operation.

***Keywords*—**Space telemetry monitoring, multivariate analysis, PCA algorithm, space operations.

I. Introduction

RELIABILITY, availability, and safety are critical requirements in space mission operations. Moreover, flight controllers are responsible not only for operating their designated spacecraft subsystems to meet mission intentions but also for monitoring those subsystems to ensure that they are operating appropriately.

Data-driven process monitoring or statistical process monitoring (SPM) applies multivariate statistics and machine learning methods to fault detection and diagnosis for space operations, which has become one of the most rich areas in research and practice over the last two decades. Based on methods from the multivariate statistical analysis, SPM has found wide applications in various processes, including space operations. The situation is greatly complicated by the fact most of the techniques representing different modalities are complex and have a black box impacts. So, due to the data-based nature of the SPM methods, it is relatively easy to apply to real processes of rather a large scale comparing to other methods based on systems theory or rigorous process models.

Space missions are characterized by large-scale complex operations that are well instrumented with a multi-level control hierarchy, making it a suitable place to apply the SPM methodologies. Disturbances and variabilities in operation conditions are the critical obstacles to overcome to make quality operations. The task of data-driven process monitoring is to detect such an abnormal situation and diagnose the root-cause early. SPM capabilities are to extract vital information from both huge archived data and real-time operations data. The Applications of SPM methodology provides better knowledge and more accurate characterization of changes and disturbances in space systems operations.

The paper represents a statistical fault detection algorithm based on the PCA latent space model. The algorithm introduces a practical approach for monitoring and diagnosis that includes: (i) fault detection; (ii) fault identification or diagnosis and quality monitoring. The tasks of the algorithm are to model, analyze and identify key contributors to anomalous events automatically which lead to characterize the spacecraft (ADCS) behavior. However, this approach does not build a causality direction between variables rather it builds a correlation direction inside a bounded region. Hence, it represents an efficient tool as a first step for process monitoring through the analysis of existing information. The contributions of this design work can be itemized as:

1) To the best of the authors' knowledge, this is a new application to model and analyze the ADSC spacecraft telemetry using the unsupervised learning algorithm PCA.
2) The algorithm possesses the modeling of the data in the X-space where the advantage of the contribution and control plots can be seen. These plots facilitate the detection of the variables responsible for any process and monitor key process variables and quality over time.

The remainder of the paper is organized as follows. We introduce an overview of related work to the area of research in Section II. The proper use of data-driven models based on the multivariate latent approach concept is discussed in Section III. ADCS configuration is presented in Section IV. Then, the main details and theoretical analysis of the algorithm are discussed in Section V. The performance of the algorithm on ADCS telemetry data and the analysis results are compared with the well-known multivariate data analysis

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software known as soft independent model for class analogy (SIMCA-P) developed by Umetrics are shown in Section VI and VII. Finally, we conclude in Section VIII.

II. Related Work

Archived spacecraft telemetry data contain a wealth of information about complex system behavior, so recent development techniques for monitoring and anomaly detection make it possible to examine this archived data and extract embedded information to produce advanced system health monitoring applications [1]. Researchers have devoted considerable effort to the application of various different soft computing methods to develop heath monitoring systems (HMSs) for space operations and the methods used include neural networks, multivariate statistical approaches and data mining techniques. These methods can provide important tools for the field of intelligent monitoring which can learn, adapt, and make decisions concerning the system they are in charge of [2].

T. Yairi et al. [3] evaluated a variety of dimensionality reduction algorithms and compared them without using the cross-validation. Regarding the authors' point of view, using the cross-validation might be too time-consuming when the training set or the number of classes is large.

I. Verzola et al. [4] clarified that a space operations are often based on a reactive model. The main drawback of this model is the unfeasibility of preventing the failure executing preventive actions to avoid the expected faulty condition. Moreover, their work describes a study on a possible proactive model to deal with failures based on techniques from statistics and machine learning to identify future trends of the object to foresee the behavior of the system. However, the research work did not give the predictions in real-time that to be checked against a set of pre-defined failure probabilities thresholds.

J. MacGregor et al. [5] established the potential of applying multivariate methods in monitoring and fault diagnosis contrasted with many other data-driven techniques. The authors declared that black-box models such as Artificial Neural Networks (ANNs) and Hidden Markov Models (HMM) and statistical classification techniques such as Discriminant Analysis (DA) and Support Vector Machines (SVMs) are fallen within the class of regression methods/classifiers that provides no allowance for modeling the X-space. In addition, those techniques have a limited capability to interpret of full rank data, to handle missing data and to test for outliers in new data. Even though they recognize that methods can be useful in some cases.

J. Peng et al. [6] proposed a fault diagnosis method for key components of satellite called anomaly monitoring method (AMM), which is made up of state estimation based on multivariate state estimation techniques (MSET). This method applied to the satellite power subsystem, and the analysis of failure applied on lithium-ion batteries (LIBs). Only two parameters were selected as the key parameters of AMM, so either an in-depth analysis failure of LIBs is conducted or more influencing parameters were considered. S. Lindsay et al. [7] applied several supervised learning and unsupervised methods to four different spacecraft SOH scenarios after the data pre-processing step. However, real-time anomaly resolution remains a potential research area to be examined.

The simplicity of multivariate statistical analysis approach is that there is no need for a fundamental model of the system and only data from normal operation needs to be used, which is generally available in some form for most machines. Among the approaches used in the multivariate analysis are: two projection methods called principal component analysis (PCA) and projection to latent structure (PLS). Many applications of these two techniques have been successfully applied in other fields of process monitoring. Among the approaches used in multivariate analysis the PCA is a well-known data-driven multivariate statistical tool used in many applications particularly the fields of process monitoring and diagnosis [8]-[10].

III. Multivariate PCA Basic Theory

The principle component analysis (PCA) is a quantitatively rigorous unsupervised learning technique that used in extracting information from data and is widely used by scientists and engineers in various disciplines such as in process monitoring, data compression, image analysis, as well as in fault detection decades ago. The method produces a compressed statistical model that gives linear combinations of the original variables that describe the major trends in the Tta sets in terms of capturing the variance of the data. The PCA is a mapping that produces new variables that are uncorrelated with each other and are linear combinations of the original variables and also preserving the correlation structure between the original features.

The "aggregate variance" of the whole set of variables remains unchanged from before to after the mapping, but the variance is redistributed so that the most is in the first mapped variable, the next largest amount goes to the second mapped variable and the least to the last transformed variable. These new variables are called the principal components [13]. The utility of this method lies in the ability to explain as much of the total variation in the data as possible with the least number of principal components (new variables). The point that needs to be stressed is that the data can be reduced to a size that is more manageable but contains the features that are often of interest. PCA extracts a score matrix, T, and a loading matrix, P, from X. These matrices have the following dimensions [9]-[11]:

$$X: N \times K \qquad T: N \times A \; P: K \times A \tag{1}$$

The first column of T and P are called by their shorter forms, $t_{1,}$ and p_1 respectively. PCA decomposes the data matrix X to the sum of the products of K($K \leq \min\{m, n\}$) pairs of vectors and a residual matrix, E:

$$X = t1p_1^T + t2p_2^T + ... + tkp_k^T + E \tag{2}$$

where ti = scores vectors, Pi= loadings vectors (eigenvectors of the covariance matrix) , E= residual matrix.

So, the score vectors in the score plot represent the principle component (new variables) ti and Pi the loadings vectors represent (eigenvectors of the covariance matrix) or variables coefficients. In addition, the score and loading plots are superimposed; this means that variables lying in each quarter of the loading plot are contributing to the changes in the observations in the score plot. The residual matrix contains that part of the data not explained by the PCA model. The N-K t, p vector pairs not in the model are associated with "noise" the uncontrolled process and or instrument variation arising from random influences. A more in-depth discussion, which also highlights some geometric concepts of PCA, can be found in [12]. The algorithm used to calculate the PCA is the nonlinear iterative partial least squares algorithm (NIPALS) [9]-[11].

IV. System Configuration

The spacecraft telemetry data contains a variety of information including myriad sensor measurements. Anomaly detection techniques described in the previous section was applied to the attitude determination and control system (ADCS) of remote sensing spacecraft owned by Egyptian National Authority for Remote Sensing and Space Sciences (NARSS).

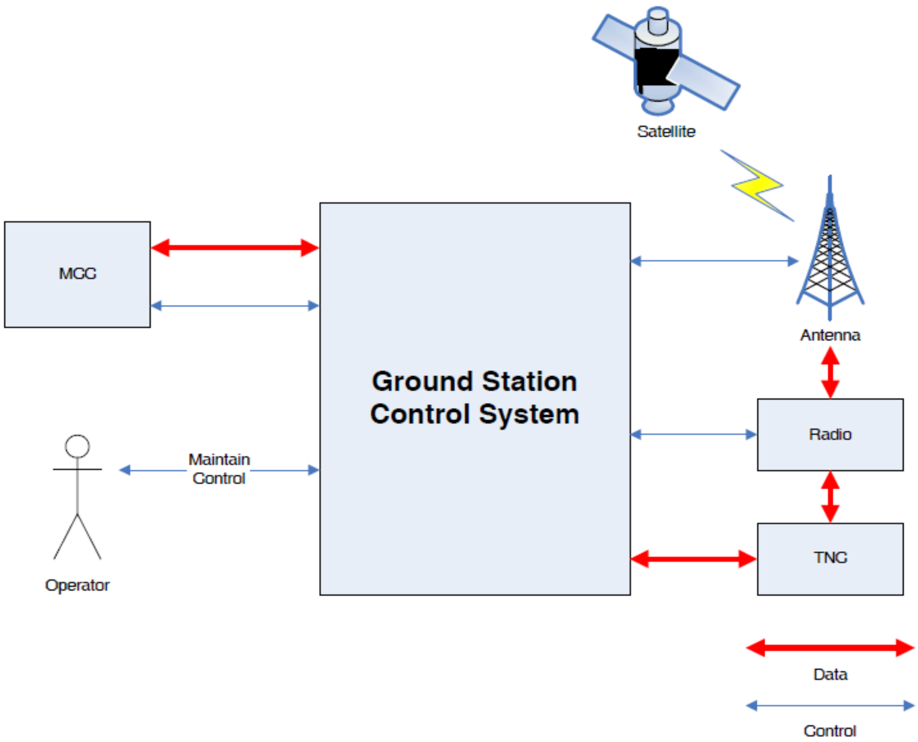

Fig. 1 Structure diagram of the space system

The main purpose of ADCS is to orientate the main structure of the spacecraft at the desired angle(s) within required accuracy. The attitude of spacecraft can be represented in different ways with a set of variables such as directions cosine matrix (DCM), Euler angles, angular velocity and quaternion (also known as Euler parameters)… etc. ADCS composition contains angular velocity meter (AVM) blocks that are mounted in such a way that three AVMs measuring axes are collinear to body-fixed axes, and the fourth one is a backup. The system also had a magnetometer (MM), magnetorquers (MT), reaction wheels (RW) and star sensor. Fig. 1 shows the space system structure.

V. Algorithm Peculiarities

The principle component analysis (PCA) algorithm is mainly applied as an unsupervised learning tool for spacecraft telemetry data. The algorithm strategy is to manage operation status acquired via (ADCS) telemetry data to provide efficient monitoring for the system above. The methodology operates in two phases; first, the training phase learns the model using the available training data. Then, the next phase trends and clusters the data instance as normal or an outlier using the model. The framework of the algorithm enumerated in the following steps:

1) Auto-scale the training data to unify the influence of the features before building the model. These measures allow the model to decide the effect of each variable regarding their real influence.
2) Train PCA model using the training data (Training samples X = [X1, X2,., Xn], then standardize the data, further calculate the variance of matrix (X) which measure of the spread of data in a given data set (one

dimensional concept):

$$\mathrm{Var(X)} = \frac{\sum_{i=1}^{m}(X_i-\bar{X})(X_i-\bar{X})}{m-1} \tag{3}$$

where, $\bar{X}$ mean of the set X and m: sample number and Λ= ($\lambda 1$ >.. > λm) is a diagonal matrix containing the eigenvalues in a decreasing order ($\lambda 1 > \lambda 2 >.. > \lambda m$). Further, to calculate the covariance matrix (S) of data Matrix (X), so if the data matrix-X has m-rows and n columns, then the covariance matrix S is equal to:

$$S = \mathrm{cov}(X) = \left(\frac{1}{m-1}\right)(X^T X) \tag{4}$$

Then, choose how many PCs are used. The validity of the PCA model depends on a good choice of how many principal components (PCs) are retained. Underestimating the number of PCs can leave out important variations in the data which degrades the prediction quality of the PCA model. Overestimating the number of PCs, on the other hand, introduces noise that masks some of the important features in the data.

3) Construct the model for exploratory and trend the data under diverse operating conditions.
4) Compute the ranking of all features with a certain criterion in term of their contribution to trends and clustering. One can note that the ranking criterion for the trends and clustering of features is based on the normal vector of the hyper-plane.
5) Finally, the model is used along with one of the detection guides to detect faults for new data samples (if the detection index falls outside the control limits, which are defined by the thresholds associated with these indices). The Hotelling's (T^2) statistic measures the variations in the principal components at different time samples. For new testing data, when the value of T^2 exceeds the value of the threshold, ($T^2\alpha$) a fault is declared. The (Q) statistic or squared prediction error (SPE) measures the projection of a data sample on the residual subspace, which provides an overall measure of how a data sample fits the model. When a vector of new data is available, the Q statistic is calculated and compared with the threshold value (Qα). If the confidence limit is violated, a fault is declared. The value of the threshold is calculated based on the assumptions that the measurements are time-independent and multivariate normally distributed. The Q fault detection index is very sensitive to modeling errors, and its performance largely depends on the choice of the number of retained principal components). Fig. 2 shows the framework of the PCA monitoring algorithm.

VI. Model Building

The concept of the model depends on using of operation variables. Let X-matrix includes variables containing information from the sensory data. First, the data were mean centered and scaled to unit variance. Second, control limits in the latent space were established using F-distribution based on reference distribution provided by the dataset. In addition, t1 and t2 are the first two principal components that capture most of the variance in the X-matrix. Fig. 3 illustrates how the score plot is built for a simple case 3-variables and 2-scores. After determining the direction of maximum variation by iterative steps, one might rotate the new plane determined by the new score variables t1 and t2 and then monitor the change of the new observations in the reduced dimensional space during space operations.

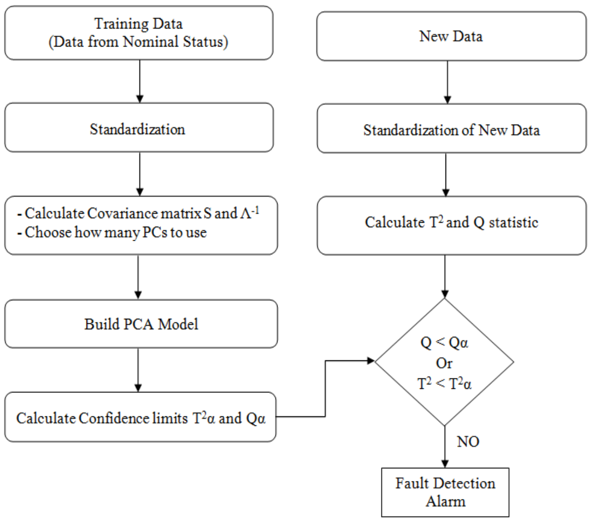

Fig. 2 PCA Fault detection algorithm framework

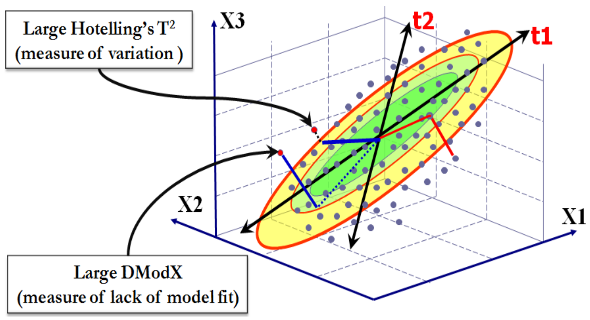

Fig. 3 Establishing score plot for three variables

The scenario of spacecraft operation uses a total of "16" features to generate the input matrix "X", which means that the original data has "16" dimensions "D = 16". These features represent the root mean square of the time domain records of the sensory signals measurements regarding spacecraft roll, pitch, yaw angles, angler velocity and quaternion's ---, etc., Models are built using the new principle component analysis (PCA) algorithm and compared with SIMCA-P software developed by Umetrics [9]. PCA finds latent directions that maximize the variance of the process. The multivariate model is a linear model given in matrix form by $X = TP^T + E_A$. However, there exist non-linear PCA versions even by augmenting the original matrix with the non-linear factors or by building a non-linear relation between score factors [14]. The models are established using a set of telemetry data sampled from the spacecraft operation for two days that represents the nominal and off-nominal operations of (ADCS). During this period, a system anomaly was reported due to angler velocity meter in Z-direction (AVMz) malfunctioning and the reserve (AVMr) were used instead of the faulty one. In addition spacecraft high rate damping mode (detumbling mode) occurs. If the fault mentioned above will be repeated the spacecraft will acquire the detumbling mode more than the design specifications and regarding experts experience this mode is very critical because it could be lead to spacecraft losses.

VII. Results and Analysis

The key target in building (PCA) models is data preparation, scaling and selecting the number of principal components. First, data must be in tab enclosed text format with no headings or extra characters before entering into MATLAB. The PCA is unsupervised learning approach that does not have class labels on training data and sometimes does not include the number of classes. The approach is based on using an available database that gives an acceptable level of process quality to build the monitoring system and then the model can reveal both smooth time trends and sudden shifts in the telemetry of normal operation. Consequently, the first model is generated using the proposed PCA unsupervised algorithm and compared with SIMCA-P software, so a clear supervision for the data can be attained. The telemetry with "777" observations from nominal operation as training set for different features values used to develop the PCA model. Fig. 4 shows a scatter plot of the two score vectors t1 and t2 of the PCA algorithm (new mapping variables). The model illustrates a clear direction of the data that indicates the trends. Fig. 5 demonstrates the results acquired by SIMCA-P software. To get better supervision of the data another attempt has been made by augmenting the X-matrix using transformation and unit scaling of variables. The model is fitted by cross-validation to get a two-component model with R2X(cum): 0.893, Q2(cum): 0.812. The model shows a good percentage of explanation of the X-variables R2X(cum), together with a good percentage in the prediction ability as shown by Q2(cum) and the both models results have a remarkable agreement.

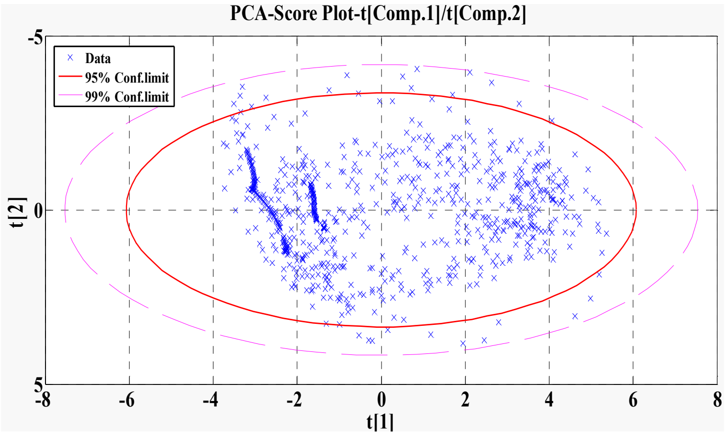

Fig. 4 PCA score vectors (t1 and t2) of the algorithm using nominal process data

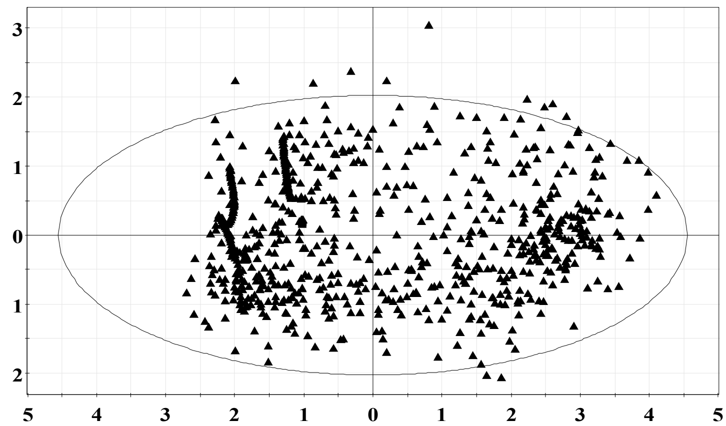

Fig. 5 PCA score vectors (t_1 and t_2) of SIMCA-P software using nominal process data

The second model was validated to the spacecraft telemetry, and it has been built by using "810" observations for both nominal and faulty operations of (ADCS) "777 normal data", "33 faulty data". As we mentioned in Section III and referred to (NIPALS) algorithm that $T=P^TX$, so the score vectors in the score plot represents the principle component (new variables) ti and Pi represent the loadings vectors (eigenvectors of the covariance matrix) or variables coefficients. Figs. 6 (a) and 7 (a) show scatter plots of the two score vectors (t1 and t2) for both our PCA algorithm and SIMCA-P software that provide a clear vision of the dispersion of the data, with two main groups: normal and faulty data. This clustering is shown by manually highlighted by black line clusters in the plot (for visual purposes). The analysis proves the capability of the model to create unique data clusters and compare the characteristics of each one. In addition, a clear interference can be detected between two groups in observation "N 788" and it is shown by manually highlighted with red dotted circle in the score plot and the explanation for this will be introduced afterwards. Additionally, another attempt has been made by expanding the X-matrix with square terms, cross product and cubic terms between the important variables that represent the most effective influence regarding the fault. Furthermore, the model is fitted by cross-validation to get a two-component model with R2X(cum): 0.882, Q2(cum): 0.793. More study is conducted by examining the loading plots of both PCA algorithm and SIMCA-P software to investigate the relationships between the different variables. Figs. 6 (b) and 7 (b) show the loading plots that clarify the relations between variables. As we explain before the score and loading plots are superimposed, so by investigating the loading plots one can detect directly which variables are more responsible for affecting a specified group of data in the score plot. Finally, assessment of both models results shows a significant agreement.

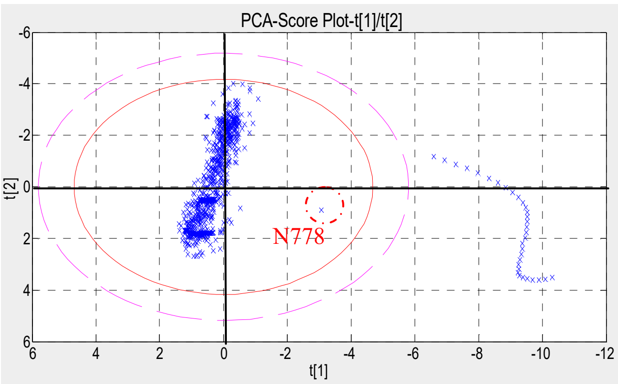

Fig. 6 (a) PCA algorithm score plot using the training dataset

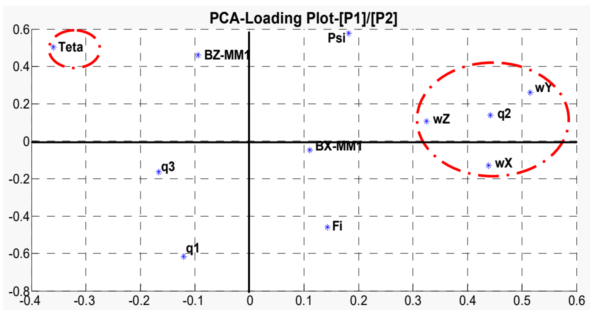

Fig. 6 (b) PCA algorithm loading plot using the training dataset

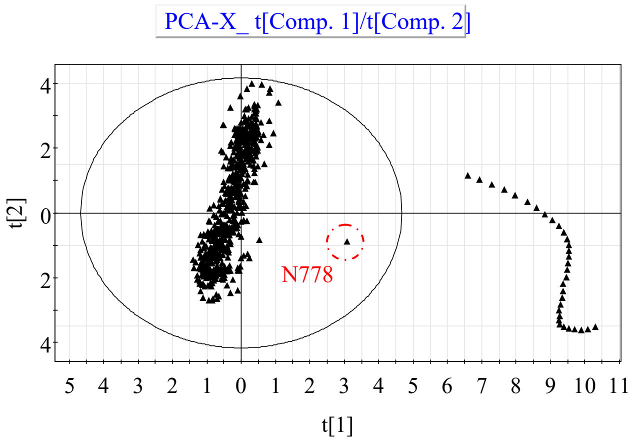

Fig. 7 (a) SIMCA-P software score plot using the training dataset

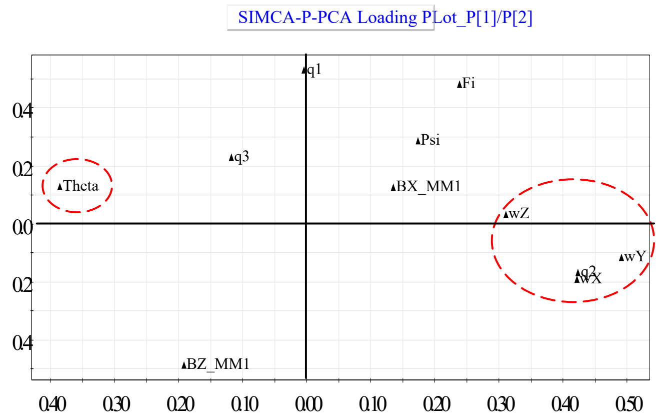

Fig. 7 (b) SIMCA-P software loading plot using the training dataset

From Figs. 6 and 7 one can notice how angular velocities (ωx), (ωy), (ωz), quaternion (q2) in the left corner of the loading plot contribute to the left swarm (faulty states) of data in the score plot. In other words, these variables are directly correlated with the faulty states while the pitch angle (Theta) is inversely correlated with them. A further investigation carried out by using the contribution plot named variables importance to projection (VIP) bar plot Fig. 8. The plot explains the anomaly identification across the features deemed most critical in determining the overall health status of the process operation and shows that the variables mentioned above ωx, ωy, ωz, q2, and Theta are most critical. More investigation was carried out using contribution plots which represent the unexplained variation ("residuals") in the model and can be used to define a control limit in a direction perpendicular to the PC-model hyperplane and detect processes upsets (spikes in telemetry data that couldn't be observed by scatter plots) by determining moderate outliers. Figs. 9 and 10 demonstrate both our PCA contribution plot and SIMCA-P plot that is named distance to model X (DModX). From both plots, one can note that the most of the observations from "N1" to "N777" used to train the model are inside or nearly inside the model critical distance (D-Critical 0.05) which indicates that in this time interval the process is fairly stable, and no new process event is recognized.

However, the last observations from "N778" to "N810" don't fit the model well, and indicate that a new process behavior has become establish and ought to be scrutinized more closely and observation "N778" is farthest away from the model plane displays largest portion of unexplained variation.

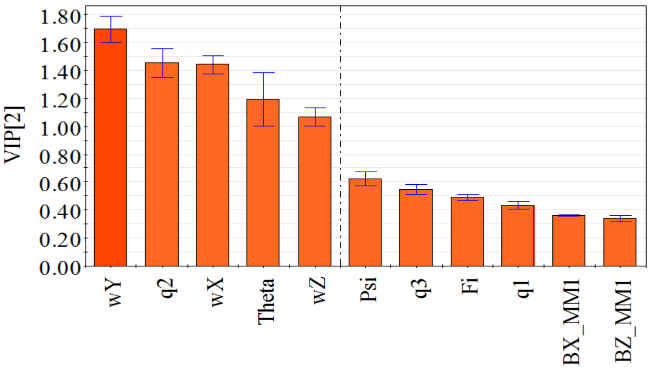

Fig. 8 SIMCA-P variables importance in projection

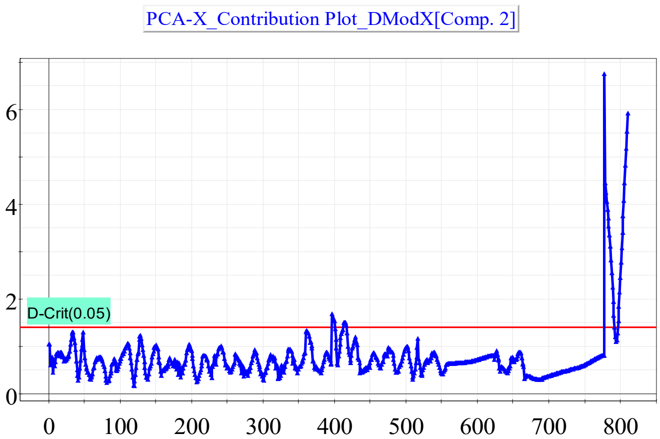

Fig. 9 SIMCA-P DModX contribution plot

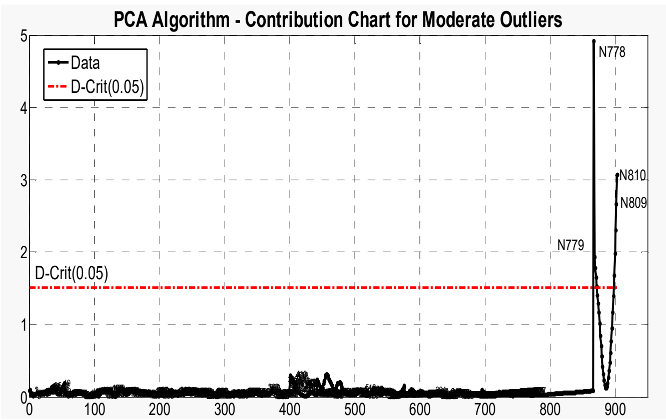

Fig. 10 PCA algorithm contribution plot

Further investigation can be carried out using control charts. Fig. 11 shows the control Hotelling's T^2 and DModX (model residual) plots with the training set. A clear advantage is realized from modeling the X-space over the present approaches the Hotelling's T^2 chart failed to detect this shift but is alarmed through the model residual DModX starting from observation "N778". One can observe that the score plot model cannot differentiate between the faulty telemetry "N778" with the others normal ones in both models results acquired by SIMCA-P and the proposed algorithm. The explanation for this is the difference in goal between supervised and unsupervised learning methods. The unsupervised PCA is a well-known multivariate technique for exploratory data analysis. But, supervised pattern recognition techniques differ from PCA in that the goal is to detect similarities between objects and find groups in the data on the basis of calculated distances, whereas PCA does not focus on how many groups will be found. Consequently, Also PCA do not use information related to predefined classes of objects. On the other hand, supervised pattern recognition requires a priori information on the set of samples that is used for classification purposes. Gathering both control and residual contribution charts are very informative and enables strong and moderate process outliers to be considered simultaneously.

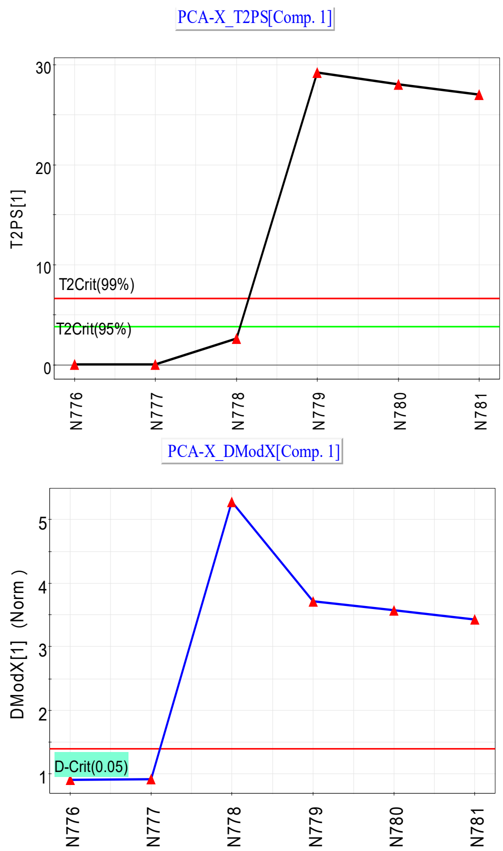

Fig. 11 Monitoring system built for alarm

Fig. 12 explores the contribution bar plot that is used to understand which variables contribute most strongly to an observed process change. One can notice that the angular velocity of spacecraft ωy , quaternion elements q2 of the satellite orientation in orbital coordinate system (OCS) and the pitch angle (Theta) giving an alarm on the occurrence of the faulty state due to high angler velocity which caused by the beginning of high rate damping mode (detumbling mode) occurs. In addition, the dissimilarity between faulty observation "N778" and the rest faulty ones is a critical intention. This unique direction is regarding to that faulty telemetry "N778" has the higher effect of the pitch angle (Theta) instead of reverse effect in others faulty telemetry and this is reasonable, due to the beginning of occurrence of high rate damping mode of the spacecraft.

Additional analysis using multivariate control charts are crucial objective because the contribution plots will not explicitly indicate the cause of this shift provides good insight into plausible causes or variables related to the causes. To detect special events, control chart technique is routinely used to monitor key process variables and quality over time. So, the proposed algorithm has the capability to detect large changes like a shift in average or general drift overtime via investigating the telemetry data over time. Both Figs. 13 and 14 show that the process shifts could be tackled using the control chart of the PCA algorithm and SIMCA-P "Shewhart control chart " that are used as an early warning trend monitor. Gathering both control and residual contribution charts are very informative and enables strong and moderate process outliers to be considered simultaneously.

VIII. Conclusion

The unsupervised learning principle component analysis (PCA) algorithm is introduced to monitor the spacecraft operations status via a practical application on attitude determination and control subsystem (ADCS). The algorithm is based on the multivariate projection technique and applied to spacecraft telemetry data to manage ADCS operations and overcome faulty state. The algorithm exploits telemetry data for model building and testing. The analysis results clarify that the algorithm has the capability to supervise the major trends in the data and compares the characteristics of each one and capable to correlate the clusters with low cardinalities to their corresponding trigger events. Furthermore, the analysis results acquired by our algorithm and soft independent model for the class analogy (SIMCA-P) software were compared together and show an evident agreement. The algorithm proves that it can be used as an effective tool for monitoring ADCS operations status and deals with multiple process states.

In the near future, we aim at adopting and evolving the approach into a more powerful tool by extending the work to be implemented for more than one faulty system and coupled with supervised learning techniques like support vector machines (SVMs) and projection to latent structure discriminant analysis (PLS-DA) to solve the relevant problems.

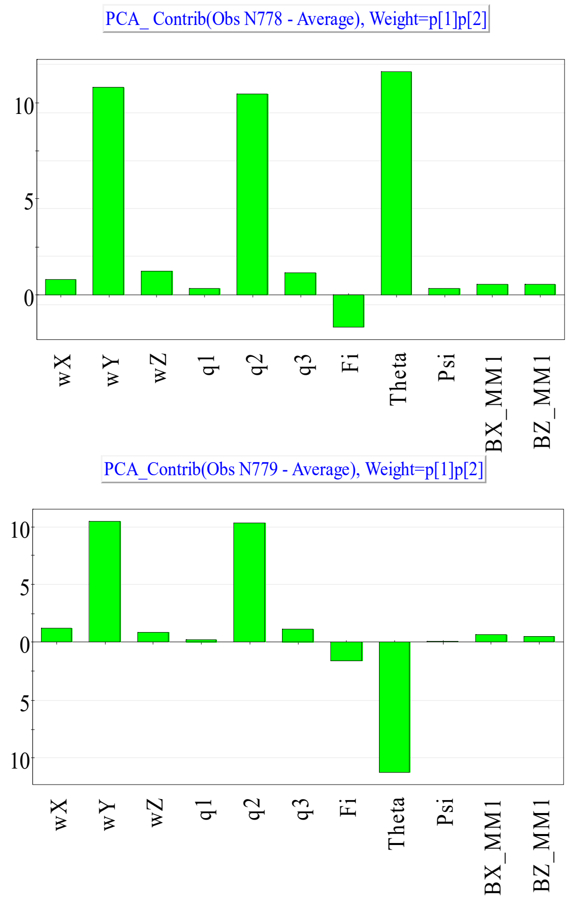

Fig. 12 Contribution to variables weight plot

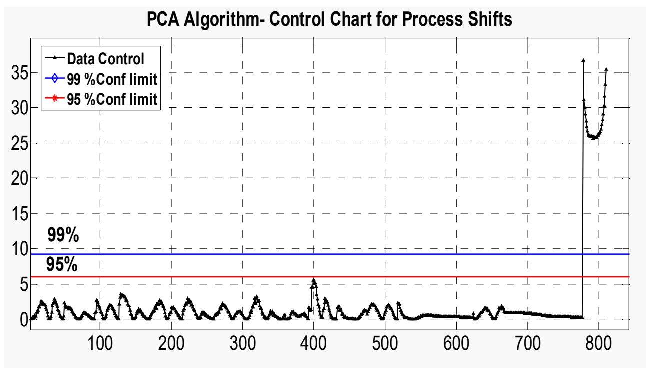

Fig. 13 PCA algorithm control charts for process shifts

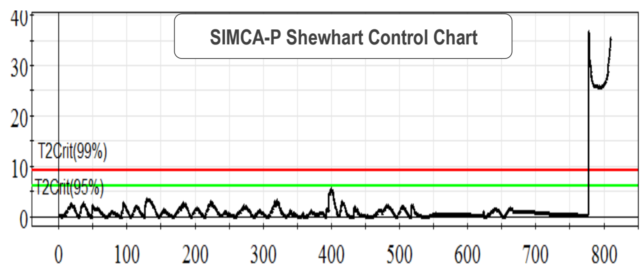

Fig. 14 SIMCA-P Shewhart control charts for process shifts

REFERENCES

[1] D.L. Iverson, R. Martin, M. Schwabacher, L. Spirkovska, W. Taylor, R. Mackey, and J.P. Castle, "General Purpose Data-Driven System Monitoring for Space Operations," *in Proc. of AIAA Infotech @ Aerospace Conference*, Seattle, WA, October 2010.

[2] D.L. Iverson, "Data Mining Applications for Space Mission Operations System Health Monitoring," *NASA Ames Research Center, Moffett Field, California, 94035 Space Operations Conference*, 2008.

[3] T. Yairi, M. Inui, A. Yoshiki, Y. Kawahara, and N. Takata, "Spacecraft Telemetry Data Monitoring by Dimensionality Reduction Techniques," *in Proc. SICE Annual Conference,* Japan, 2010.

[4] I. Verzola, A.E. Lagny, and J. Biswas, "A Predictive Approach to Failure Estimation and Identification for Space Systems Operations," *in Proc. 13th international conference on space operations,* Pasadena, California, USA, May 2014.

[5] J. MacGregora, A. Cinarc, "Monitoring, fault diagnosis, fault-tolerant control, and optimization: Data-driven methods," *Journal of Computers and Chemical Engineering,* vol. 47, June 2012.

[6] J. Peng, L. Fan, W. Xiao, and J. Tang, "Anomaly Monitoring Method for Key Components of Satellite," *Scientific World Journal,* vol. 2014, Article ID 104052, January 2014.

[7] S. Lindsay, and D. Woodbridge, "Spacecraft State- of-health (SOH) Analysis via Data Mining," *in Proc. 13th international conference on space operations,* Pasadena, California, USA, May 2014.

[8] S. Wold, K. Esbensen, and P. Geladi, "Principal component analysis", *Chemometrics and intelligent laboratory systems,* vol. 2: 37-52, 1987.

[9] J.E. Jackson, *A User's Guide to Principal Components*. Wiley, New York, 1991.

[10] S. Wold, M. Sjostrom, and L. Eriksson, "PLS-regression: a basic tool of Chemometrics", *Chemometrics and intelligent laboratory systems,* vol. 58:109-130, 2001.

[11] L. Simar, and W. Hardle, *Applied Multivariate Statistical Analysis*. *Tech method and data technologies*. Springer-Verlag, Berlin and Louvain-la-Neuve, 2003.

[12] P.R. Goulding, B. Lennox, D.J. Sandoz, K.J. Smith, and Marjanovic, "Fault detection in continuous processes using multivariate statistical methods," *International journal of systems science,* vol. 31(11), pp. 1459-1471, 2000.

[13] T.K. Ralston, G. DePuy, and J.H. Graham, "Computer-based monitoring and fault diagnosis a chemical process case study," *Instrument Society of America Transactions ISA,* vol. 40, pp. 85-98. E, USA, 2003.

[14] Y. Zhan, and V.Makis, "A robust diagnostic model for gearboxes subject to vibration monitoring," *Journal of Sound and Vibration*, vol. 290, pp. 928–955, 2006.