Health Monitoring of Hydraulic System Using Feature-based Multivariate Time-series Classification Model

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1 Introduction

Time-series data classification is an active research area for the past decade [1]. Time series is a set of data points taken consecutively through time. It is mathematically denoted as

$$D_e(f); [e = 1, 2, \ldots, g; f = 1, 2, \ldots, t]; \tag{1}$$

e = index of various measurement at each point of time—f,
t = number of observed variables, and
g = number of observations.

In time-series data analysis, we have one variable called time. We can scrutinize this time-series data with the objective to extract meaningful statistics and other characteristics. The main goal of this time-series data is to predict the subsequent values on the basis of previous observation values. If the data has one variable, i.e., g = 1, it is referred as uni-variate. Uni-variate analysis is a very simplest form of statistical analysis. It is essentially the descriptive analysis of a single variable used

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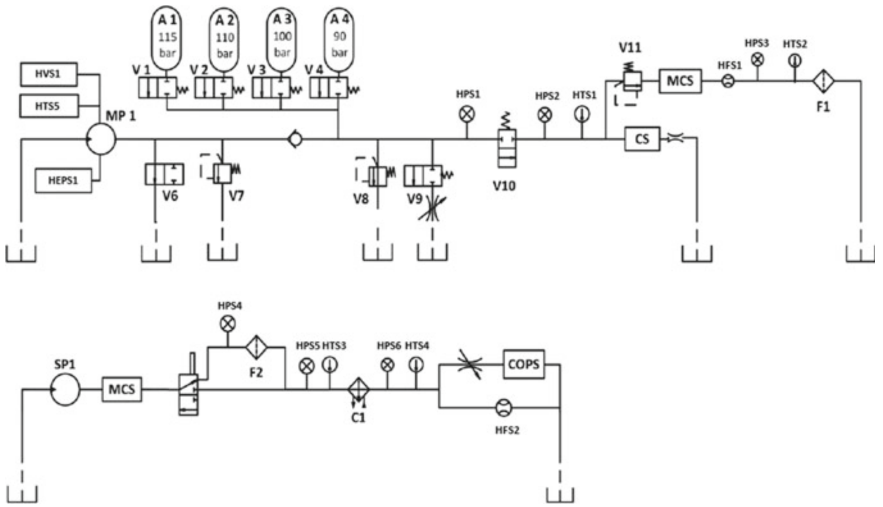


Fig. 1 Physical model of a hydraulic system used to collect training data

to describe characteristics of a sample. It is used to get the picture of how the sample looks like rather than examining their relationships and causes. If the data has one variable, i.e., $g > 1$, it is referred as multivariate.

Hydraulic systems must be contained at any rate for essential segments. There should be a compartment that stores oil and liquids, a pump that impels the liquids through the system, a valve to control the pressure and flow of the liquids inside the system, and a cylinder to change over the development of liquids into actual work. There are different segments in the middle, yet all systems must have these four [2]. Figure 1 illustrates a physical model of hydraulic test rig. The test system is outfitted with a few sensors measuring process values such as flow (HFS1, HFS2), electrical power (HEPS1), pressure (HPS1–HPS6), vibration (HVS1), and temperature (HTS1–HTS5) with standard industrial 20 mA current loop interfaces connected to a data acquisition system. Sampling rates range from 1 Hz (flow sensor) to 100 Hz (electric power/pressure) to contingent upon the dynamics of the underlying physical values.

Figure 2 illustrates an example of multivariate time series and is a hydraulic test rig data, where numerous parameters such as pressure sensors, hydraulic-(HPS1–3), motor power sensor-HEPS1, and volume flow sensor-HFS, are continually measured and stored by test rig in real time. The test rig system then executed various thousand working cycles during which distinct fault conditions were simulated in all combinations. Figure 2 shows hydraulic test rig multivariate time-series data consisting of five parameters [2].

Multivariate data classification is devised as a supervised machine learning problem mainly intended for labeling data of varying length. Each parameter is a time series, sequence of pairs (timestamp, value) [1]. Hydraulic system consists of a set of

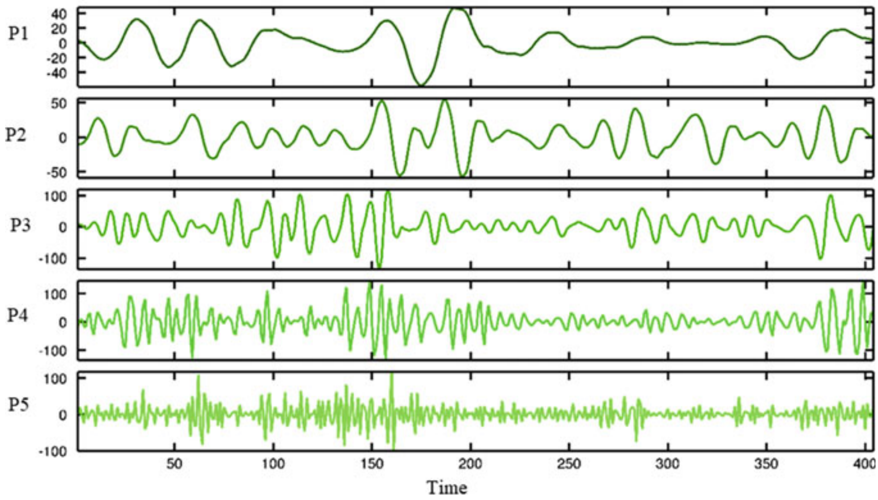


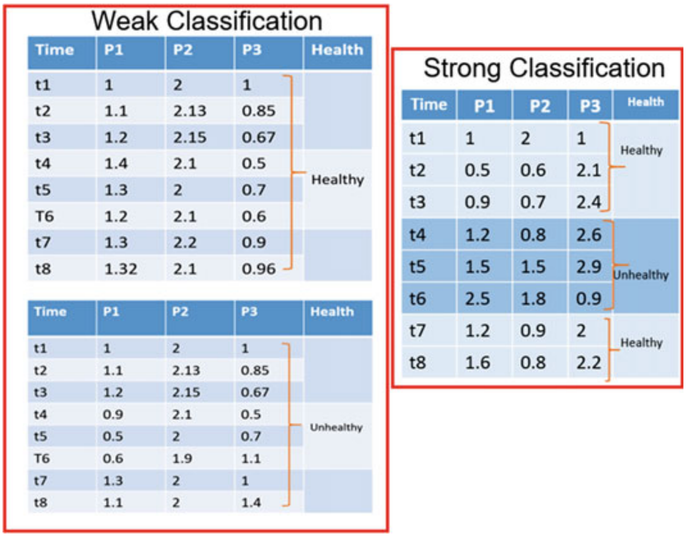
Fig. 2 A hydraulic test rig multivariate time-series data consisting of five parameters (pressure sensors hydraulic-(HPS1–3), motor power sensor-HEPS1, and volume flow sensor-HFS

parameters like HPS1–3, HEPS1, and HFS1, i.e., a multivariate time series (MTS). This system requires to be classified as Healthy or Unhealthy, in accordance with the values of the parameters [3, 4]. The time-series classification is divided into two broad categories: [1] conventional or weak classification [3] and contemporary or strong classification. Figure 3 shows weak classification, in which each succession is affiliated with only one class label and the entire succession is available to a classifier in prior to the classification. Figure 3 shows strong classification, in which each set of time-series data is organized into a different succession of classes.

The major contributions of this paper are as follows:

- In feature extraction phase, statistical features are explored. The features are extracted using a single-window approach as well as the segmented-window approach from raw sensor data with a given state of health.
- For classification phase, we come up with a window-feature-based classifier which takes the window feature of the current window into account.

The rest of the paper is catalogued as follows: Sect. 2, presents related work of multivariate classification. In Sect. 3, we introduce the proposed feature extraction and classification model. Section 4 presents the experimental results of the proposed approach and Sect. 5 concludes the work.


Weak Classification

Time	P1	P2	P3	Health
t1	1	2	1	
t2	1.1	2.13	0.85	
t3	1.2	2.15	0.67	
t4	1.4	2.1	0.5	Healthy
t5	1.3	2	0.7	
T6	1.2	2.1	0.6	
t7	1.3	2.2	0.9	
t8	1.32	2.1	0.96	

Time	P1	P2	P3	Health
t1	1	2	1	
t2	1.1	2.13	0.85	
t3	1.2	2.15	0.67	
t4	0.9	2.1	0.5	
t5	0.5	2	0.7	Unhealthy
T6	0.6	1.9	1.1	
t7	1.3	2	1	
t8	1.1	2	1.4	

Strong Classification

Time	P1	P2	P3	Health
t1	1	2	1	
t2	0.5	0.6	2.1	Healthy
t3	0.9	0.7	2.4	
t4	1.2	0.8	2.6	
t5	1.5	1.5	2.9	Unhealthy
t6	2.5	1.8	0.9	
t7	1.2	0.9	2	Healthy
t8	1.6	0.8	2.2	

Fig. 3 Example of weak and strong classification

2 Related work

Multivariate classification problem falls under two major categories: [1] distance/instance-based approach [3] and a feature-based approach. In instance-based approach, the distance between two time-series data is computed. There is an extensive survey on categories of distance measure employed for time-series classification. On the other side, feature-based approach mainly aims to represent data using a set of features or acquired properties and thus the temporal time-series problem is transformed to a static problem. For example, if we represent a time-series data using its maximum, minimum, variance, and mean, thus transforming varied length data into short length vectors which encapsulate the above four properties. Feature-based classification is most widely employed across various domains including science. This approach is mainly applied to longer time-series data like medical, electrical, mechanical, or recordings of speech signals than a short time-series pattern. Table 1 shows the list of features extracted in multivariate classification and Table 2 shows the list of algorithms used in various conditional monitoring systems. Nikolai Helwig detected sensor faults using feature-based approach and linear discriminant analysis using hydraulic dataset. A. D. Bykov applied machine learning classification approach for hydraulic system using gradient boosting, K-nearest neighbor, and SVM using hydraulic dataset. Frank L monitored health for gas turbine engine with artificial neural networks and rule-based algorithms. The data is collected by TEDANN. Yu Chen detected and diagnosed the fault of HVDC systems using extreme learning machines and bagged trees. Pallanti Srinivasa Rao et al. detected and diagnosed health of aircraft engine using ANN method. Mustagime monitored the health of aircraft engine (gas turbine) using multiple regression analysis.

3 Feature-Based Time-Series Classification Model

The modeling of the proposed framework involves two key phases: [1] feature extraction and [3] feature classification. Each of the phases is performed in two approaches: [1] single-window approach and [3] segment-window approach. **Feature Extraction:** In the current section, we explore the extraction of various statistical features from time-series data and their use in health monitoring (classification). Classification is accomplished on the basis of features extracted for each time series and not on real values. The extraction and selection of suitable features have been accepted as a significant problem. Obviously, the number of features required and nature of the feature (global or local) depend on their discriminating quality. The prime characteristics required for identified features are ease of computation, invariant to noise, and transformations. For multivariate data, and more especially for hydraulic systems data, we propose the use of statistical features, which are commonly used in systems health monitoring.

Algorithm 1 shows the window-feature-based classifier model. The first step in feature extraction is to divide the original noise-free multivariate time-series data T_o into a set of smaller sized window segments $W_i = W_1, W_2, W_3, \ldots, W_n$. The entire duration is divided into 14 windows of dissimilar size. For each current window W_i extract eight statistical features—sum, median, mean, length, standard deviation, variance, maximum, and minimum values from five given input parameters—HEPS1, HFS, HPS1, HPS2, and HPS3. In our paper, we have explored the window label WF_i and it is added as feature value. Hence, for each window W_i nine features are extracted, and this is repeated for 14 windows, for 5 parameters.

Each parameter has 6000 samples and 2205 instances, and these 6000 samples are divided into 14 windows. For each window, we generate 2205 × (8 statistical features + 1 window feature + 1 label) = 2205 × 42 feature map. Since we have 14 windows and 2205 instance for each window (14 × 2205 = 30870), the training data size is 30870 × 42. The test data given to the model is noise-induced test data (high-level, medium-level, and low-level noise). In the traditional model, the features are extracted from the entire duration and hence we treat this to be single-window feature extraction. In this research paper, we compare our approach through the traditional approach which uses single-window feature extraction. Window-feature-based classifier is very simple, they improve classification accuracy and consistent across all three noise levels. Decision tree classification technique is used to classify the time-series data.

Table 1 Review of features extracted in multivariate classification

Year	Author	Extracted features	Datasets
2001	Nanopoulos et al. [5]	Mean (M), skewness (SK), kurtosis (K) and standard deviation (SD)	CCP data
2003	Morchen et al. [6]	Wavelets and Fourier features	Energy preservation tests
2006	Wang et al. [7]	non-linearity, skewness, periodicity, kurtosis, self-similarity, seasonality, serial correlation, chaos, and measures of trend	Benchmark time-series datasets
2009	Ye and Keogh et al. [8]	Shapelets are time-series succession which are in some sense, maximally representative of a class	Benchmark time-series datasets
2013	Deng et al. [9]	Mean (M), trend (T), and spread (S) in local data intervals	Benchmark time-series datasets
2014	Fulcher et al. [10]	Gaussianity, auto-mutual information, spread, outlier properties, auto-correlation, location, entropy, power spectrum features, Lyapunov exponent estimates, sliding window measures, surrogate data analysis prediction errors, the dimensions of correlation	Trace dataset, Wafer dataset from UCR time series
2014	Esmael et al. [11]	Discrete Fourier transform, piece-wise linear approximation, Discrete wavelet transform, piece-wise aggregate approximation, symbolic aggregate approximation, adaptive piece-wise constant approximation, and singular value decomposition	Benchmark time-series datasets
2015	Helwig et al. [12]	signal shape (position of max value, slope of linear fit) and distribution density characteristics (skewness, variance, kurtosis, and median)	Hydraulic dataset
2015	Helwig et al. [4]	Statistical moments median (Me), variance (V), skewness (Sk) and kurtosis (K) and signal shape parameters (fit of slope, the position of max value)	Hydraulic dataset
2015	Helwig et al. [2]	Skewness, Max features for oil aeration monitoring: variance, median	Hydraulic dataset
2017	Adams et al. [13]	Deep feature extraction using auto-encoder, mean, standard deviation, skewness, and kurtosis	Hydraulic dataset
2019	Chawathe et al.	Mean, variance, skewness, and kurtosis	Hydraulic dataset

Table 2 Review of algorithms used in conditional monitoring

Author	Title	Algorithm used	Dataset
Helwig et al. [12]	Detecting and compensating sensor faults in a hydraulic condition monitoring system	Statistical feature extraction, linear discriminant analysis feature selection	Hydraulic dataset
Bykov et al. [14]	Machine learning methods applying for hydraulic systems states classification	Gradient boosting, K-nearest neighbor, support vector machine	Hydraulic dataset
Greitzer et al. [15]	Gas turbine engine health monitoring and prognostics	Artificial neural networks, rule-based algorithm	Data collection by TEDANN (Turbine Engine Diagnostics using Artificial Neural Networks)
Chen [16]	Fault diagnosis of HVDC systems using machine-learning-based methods	Extreme learning machine, bagged trees	Data from high-voltage direct current
Rao et al. [17]	AI-based on-board diagnostic and prognostic health management system	Artificial neural networks	Fighter aircraft
Yildirim et al. [18]	Aircraft gas turbine engine health monitoring system by real flight data	Multiple regression analysis (MRA), ANN	Real flight data
Lovrec et al. [19]	Online condition monitoring systems for hydraulic machines	Expert system	Hydraulic machine

4 Experimental Results

This section details the process of inducing noise and its characterization. Classifier performance on an original and noise-injected multivariate time-series data will be compared under this section.

4.1 Dataset

Nikolai Helwig et al. created test data, which was experimentally acquired with hydraulic system test rig. This rig has both cooling-filter circuit and hydraulic working connected through the oil tank [2]. The hydraulic system repeats constantly with

Input : Original Multivariate Time-series (T_o), Noisy Multivariate Time-series (T_n) of length m; **Variables**-W_i- Input Window, I-Current Iteration
Output: Succession of predicted class labels.
while *(T_o=t_1)* **do**
Divide the Original Multivariate data (T_o), Noisy data (T_n) into set of W smaller sized window segments. (where W_i= W_1, W_2, W_3, ..., W_n);
For Each W_i segment;
Do ;
1. Extract Statistical features for the current segment W_i.;
2. Get the window feature WF_i of the current window segment W_i.;
3. Generate a Feature Vector F_m by concatenating the window feature WF_i of the current window segment to W_i extracted from step:1.;
End For;
For Test T_j where j = 1, 2, 3;
Do ;
1.Call the prediction model **predict**(W_i, WF_i) which returns the status of the test class.;
End For
end

Algorithm 1: Window-Feature-Based Multivariate Time-series Classification Model

Table 3 Dataset parameter description

Sensor	Sampling rate (Hz)	Samples per sensor (one sensor)
Motor power sensor (HEPS)	100	6000
Volume flow sensors (HFS)	10	600
Pressure sensors (HPS1–3)	100	6000

load cycles for the duration of 60 s and measures sensor values such as temperatures, pressures, and volume flows while the condition of three vital hydraulic components (valve, pump, and accumulator) differed significantly. The total number of instances are 2205. Table 3 shows the sensor attributes or samples recorded with varied sampling rates.

4.2 *Noise Characterization*

Singh et al. [20, 21] and Jim et al. [22] have reported that inducing controlled noise amounts to the original data improves the performance of the model. In our study, random noise data was produced using MATLAB. Random noise (RN) array is first produced between Max(maximum) and Min(minimum) value of the parameter, at that particular instance of time. The total number of instances are 2205, out of which 1449 instances are in stable condition and 756 instances are unstable. In this research work, we have induced 600 samples (attributes) of noise data in 100 instances for each parameter (HEPS1, HFS, HPS1, HPS2, and HPS3). The noise is categorized into three levels—high-level, medium-level, and low-level noise injection. Table 4 depicts

Table 4 Noise characterization: high-level noise

Param	Samp (Hz)	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}	W_{11}	W_{12}	W_{13}	W_{14}
HEPS	100				0.12 RN	0.12 RN	0.12 RN	0.12 RN	0.12 RN	0.12 RN					
HFS	10	0.12 RN	0.12 RN	0.12 RN									0.12 RN	0.12 RN	0.12 RN
HPS1	100	0.12 RN	0.12 RN	0.12 RN									0.12 RN	0.12 RN	0.12 RN
HPS2	100		0.12 RN	0.12 RN	0.12 RN	0.12 RN	0.12 RN	0.12 RN							
HPS3	100			0.12 RN	0.12 RN	0.12 RN	0.12 RN	0.12 RN	0.12 RN						

the details of percentile of noise injected within each window for each parameter. Low-level noise represents a single parameter affected by random noise. Medium-level noise represents three parameters affected by random noise. High-level noise represents all five parameters affected by random noise.

4.3 Classifier Performance

Training data and test data are created for overall instance feature extraction and window-based feature extraction as per algorithm. Following that, decision tree is used to train and test the classifier using a tenfold cross-validation technique for both traditional approach and proposed approach. To examine the effect of noise on feature extraction and feature-level classification of multivariate data prediction. We evaluated and analyzed the working model performance on noise-free data, high-level, mid-level, and low-level noise-induced multivariate data. Three major observations are made from the experimental results.

- The classifier accuracy is >90% for both traditional- and window-feature-based classification model. Out of eight statistical features—median, standard deviation, and variance feature values are robust and correlate with fault characteristics.
- In case of low-level noise, the classifier accuracy drops down to 93% for the traditional model and 83.43% for the window-feature-based classification model, where a single parameter out of five affected by random noise.
- In case of medium-level noise, the classifier accuracy drops down to 93% for the traditional model and 80.34% for the window-feature-based classification model, where three parameters out of five are affected by random noise.
- In case of high-level noise, the classifier accuracy drops further down to 65% for the traditional model and 78.4% for the window-feature-based classification model, where all five parameters are affected by random noise (Tables 5 and 6).

Table 5 FP rate, TP rate, recall, and precision for window-feature-based classification model

Mode	Traditional model				Window-based classification model			
	FP rate	TP rate	Recall	Precision	TP rate	FP rate	Precision	Recall
Noise free	0.053	0.964	0.964	0.964	0.923	0.104	0.923	0.923
Low level	0.099	0.934	0.934	0.934	0.834	0.201	0.835	0.834
Mid-level	0.1	0.933	0.933	0.933	0.803	0.233	0.805	0.803
High level	0.658	0.655	0.655	0.431	0.784	0.263	0.784	0.784

Table 6 Classification accuracy of window-feature-based classification model

Mode	Traditional model			Window-based classification model		
	ROC area	F-measure	Accuracy	ROC area	F-measure	Accuracy
Noise free	0.965	0.964	**96.4**	0.925	0.923	**92.3**
Low-level noise	0.898	0.934	**93.4**	0.823	0.834	**83.4**
Mid-level noise	0.896	0.932	**93.2**	0.788	0.804	**80.3**
High-level noise	0.507	0.507	**65.4**	0.737	0.784	**78.4**

5 Conclusion

The impact of induced noise on multivariate time-series data prediction is very significant to quantify for precise prediction. This paper examines the effect of noise on feature extraction and classification model. It is observed that for noise-free data the decision tree classifier accuracy is $>90\%$ for both traditional and window-feature-based classification model. When all the five parameters are affected by random noise, the decision tree classifier accuracy decreases to 65% for the traditional model and 78.4% for the window-feature-based classification model. Though the window-based classifier is simple, it improves the classification accuracy significantly in the presence of noise. The results show that the enhancement in decision tree classification accuracy is about 13% compared to a traditional classifier.

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