Number 4, Volume XII, December 2017

DETECTING ANOMALOUS SENSOR DATA IN WAYSIDE DIAGNOSTICS USING ENHANCED LBP-KURTOGRAMS

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Abstract: This paper examines three different methods in comparison for discovering abnormal sensor data retrieved by acoustic and mono-axial accelerometer sensors that are employed in the environment of different train sets and passes to achieve a cost friendly wayside diagnosis in Prague metros. Proposed methodology, Local Binary Patterns (LBP) on resized Kurtogram images is superior to compared methods up to 75.8% Fisher Linear Discriminant Analysis (FLDA) for anomaly detection in the sensor data. Results may count to be promising even if combined acoustic and vibration sensor data related Kurtograms are used for individual train sets. Proposed method is considered to be the first step in order to achieve an efficient diagnosis framework in wayside vehicle diagnosis.

Summary:The research focuses on diagnosis of structural faults in railway vehicles which provides cost effective maintenance and safety. Hybrid sensor information is classified by the novel methodology; Enhanced LBP-Kurtograms which outperforms all others.

Keywords: Wayside diagnosis, local binary patterns, wavelet packet energy, detecting abnormal data

INTRODUCTION

Diagnostics is the key point that provides safety of the run of a vehicle which may be stationary or wayside, using online and offline data processing techniques. Stationary techniques are more focused on laboratory experiments whereas wayside diagnostics are more capable in determination of dynamical system faults that requires less effort than stationary test environments.

Wayside diagnostics have utmost interest of the researchers due to availability of more computational power that makes able to use of complex methods in vehicle condition monitoring. Real time or offline evaluation of sensor data may indicate possible problems related to some specific mechanical parts of a vehicle which is vital for low cost maintenance that is most likely to be superior to periodical service and testing whole components of the vehicle. In addition to cost friendly nature of wayside diagnostics, it may serve real-time monitoring of individual train sets and structures when an efficient evaluation process is maintained.

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In vibration diagnostics, it is urgent to use the methods that are suitable for vehicle environment. It is known that vehicle vibration signals in many conditions, especially in wayside diagnostics, behave non-stationary random characteristics [1]. One fast and suitable technique is short-time Fourier transform (STFT), which uses overlapping windows in time, accommodating non-stationary signals. However, this method requires several experiments of the same conditions to achieve reasonable performance. In comparison with this technique, Continues Wavelet Transform (CWT) is also employed [2].

Model based diagnostic techniques may also be found in recent literature. Kalman filter, is developed to compensate the error in the acquisition of sensor data and model parameters even if the utilized model is imperfect or noise is present in the observation environment. Although, there are some limitations in this filtering process due the lack of knowledge in covariance of the observed data [3], Kalman filter is a perfect observer and can be applied to both linear and non-linear processes. However, it requires modelling both road and multi-body in an efficient way which may be cumbersome when it comes to train sets due to the interaction of wagons and locomotive and their interaction to rail.

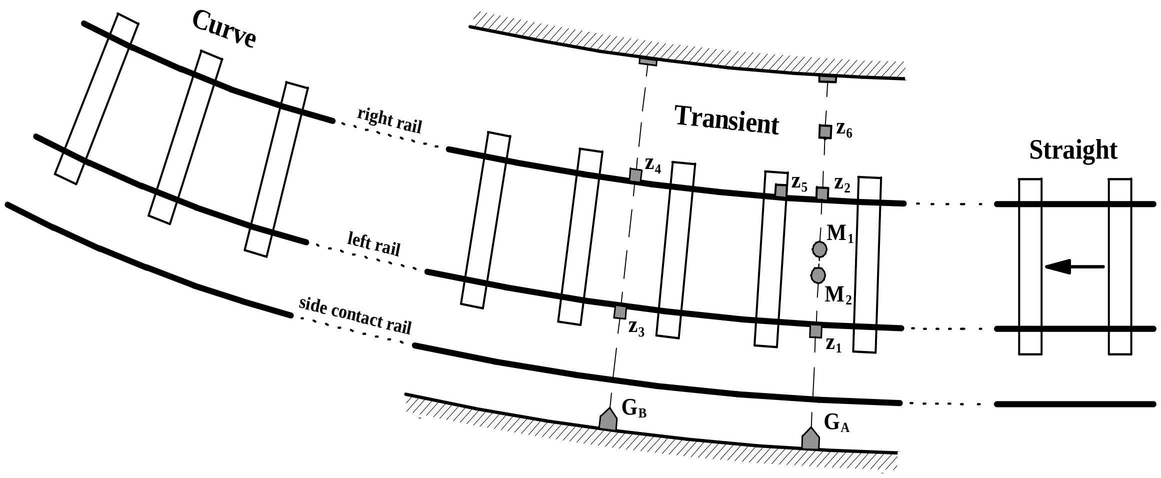
Strain based [4], accelerometer sensor based and gyroscope sensor based [5] methods are the fundamental way of measuring forces or detecting anomalous activity in the run. Other advanced techniques are also presented for specialized diagnosis of rail vehicles like sliding wheel detectors, acoustic bearing defect detection, hot box detectors, hunting of the vehicle detectors which are only limited to a particular parts of the vehicle [6].

Sensor data in many applications are degraded by environmental noise that may commonly be modelled as Gaussian additive noise or white noise. Besides, there may be some unwanted behavior in one of the components, acts as noise, which may not be easily removed or modelled because of their random characteristics. It may be smart to not to utilize further processes when the retrieved sensor data is related to environmental anomalies rather than expected signal characteristics.

This paper is organized as follows. Experiment environment and data acquisition is given in Section 1. The novel method, Enhanced LBP-Kurtogram, to identify sensor abnormalities in comparison with other methods are given in Section 2. Experimental results are demonstrated in Section 3. Finally, discussion part is presented in Section 4.

1. TEST ENVIRONMENT AND DATA ACQUISITION

In order to observe vibration characteristics and noise level, total of eight sensors are located in different locations; six one-axial accelerometers (Z1-Z6) top of feet of the rail, two microphones (M1, M2) are under the rail (same horizontal alignment with sensors Z1 and Z2. Two additional optical gates (G_A, G_B) that accompany the accelerometer sensors so ensure wheel position, targeting directly to the wheelset centers (Fig. 1) approximately 100 m from Malostranska in the direction to Nemocnice Motol metro station.



Source: Author

Fig. 1 – Sensor placement in wayside diagnostic system in Prague metro tunnel

Data is recorded by NI-CDAQ-9234 instrument which provides 51.2 kHz sampling rate on all eight channels during whole day when metros pass. Database includes all passes of the metro train sets in one day and always in the same direction just before the transition curve which make it possible to retrieve the data of the same train sets more than ones.

The database that is used in the experiment of this paper only includes M1 and Z2 signals. After having performed the thresholding in optical gates G_A and G_B, location of the wheels of each bogie are marked. These marked points are used to specify an exact window for each run of the train sets and segmentation process for signals from M1 and Z2 sensors are completed around the interval of first and last wheelset. Abnormal signals are determined empirically with the investigation of Spectrogram and Kurtogram and collected database is divided into two classes; 238 normal and 62 abnormal. It is worth to note that if any of the sensor data for a train set is too distinguishable to nominate as abnormal, data from all other runs of the same train sets from all sensors are classified as abnormal. Finally, database is equalized to 60 normal in against to 60 abnormal, preprocessed to be prepared for 6-fold cross validation in order to achieve reliable evaluation after features are extracted with the proposed methods.

2. PROPOSED APPROACHES IN VEHICLE DIAGNOSTICS

It is essential to handle difficulties due to environmental noise and model imperfections there are several methods from model based Kalman variants to time-domain methods in addition to wavelet based ones.

2.1 Kalman Filter

To suppress imperfections in modelling or environmental disturbance in the sensors, one of the very well-known method, Kalman filter, is proposed. As a commonly used filter, Kalman needs to satisfy two main conditions; stochastic process which describes system process noise, errors in the observations and the dynamic model which describes the propagation of the system in long term run. Former has an urgent outcome by means of performance due to uncertainty in covariance parameters (P, S) of process noise (Q) and observation errors (R) which affect the weighting of measurement against dynamic model.

An ideal adaptive Kalman filter ought to be able to perform accurate stochastic properties unless prior information is existed. Covariance scaling method, adaptive Kalman filter (AKF) and Multiple Model Adaptive Estimation (MMAE) have already been investigated in recent literature [7]

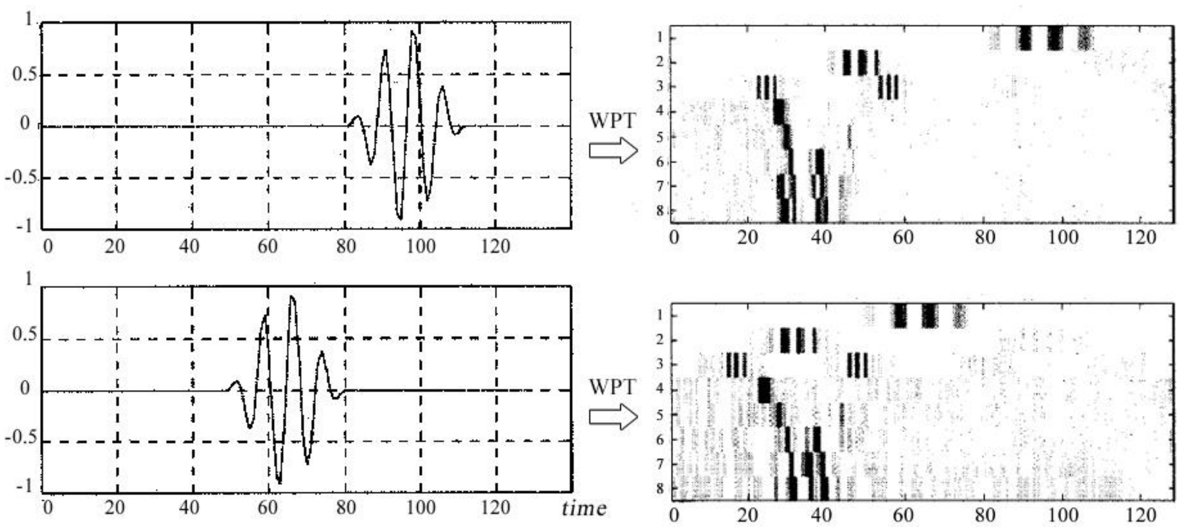
Basic Kalman filter [8] does the following according to ensure the average root mean square error is minimum to the following algorithm in Eqs. (1)-(2) for where y equals to output states of the system and L is the Kalman gain for a linearly described (n_k) system.

$$n_k = A_k n + B_k u;\ \ y = C_k n + Du;\ \ P = AP + PA^T + Q \qquad (Time\ Update) \qquad (1)$$

$$\begin{aligned} &S = (CPC^T + R)^{-1}; && L = PC^T S && (Measurement\ Update) \\ &n_k = n_k + L(y - Cn_k); && P = (I - LC)P && \end{aligned} \qquad (2)$$

2.2 Wavelet Packet Analysis

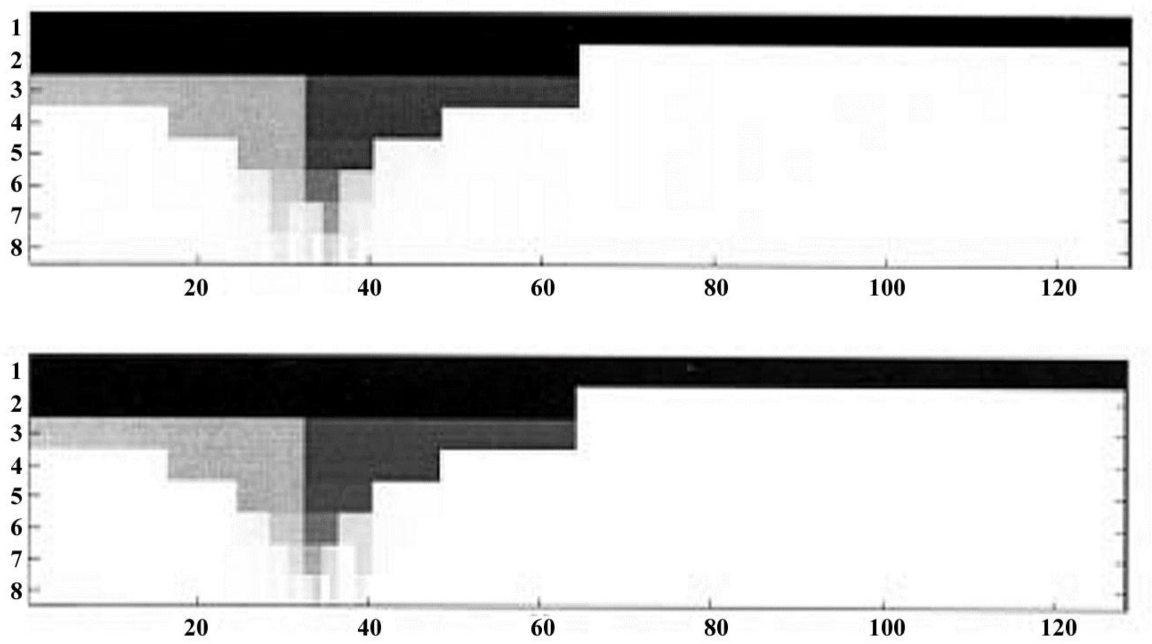
One of the very common approach to extract features from signals is so called, wavelet packet analysis, which is based on STFT, can be applied to different number of levels. Wavelet packaging divides the Fourier spectrum into sufficient size of frequency resolution, according to the given number of level L; while $n = 2^L$ where n represents number of components in the Wavelet Packet Transform (WPT).



Source: [9]

Fig. 2 – Transient signals shifted in time-domain (left), resultant eight level WPT (right)

Afterwards, carries out filtering the signal by means of low and high frequency components followed by down sampling to pass to the next level. Since wavelet packets are not time-invariant [9] that also may be seen in Fig. 2, it ought to be better to use of energy values (Fig. 3) of the packets instead especially in non-stationary signal processing.



Source: [9]

Fig. 3 – After applying three level WPE for the signals in time-shifted signals (Fig. 2)

2.3 Time Domain Features

One simple way to identify representative features of the retrieved signal is using statistical features in vehicle diagnostics [10]. These statistical features may be chosen as mean, standard deviation, median, mode, minimum and maximum statistics etc. in accordance with how much computational power is to be used. Each statistical feature can be concatenated to finalize the feature vector that may be used to train the classifiers as well as testing process.

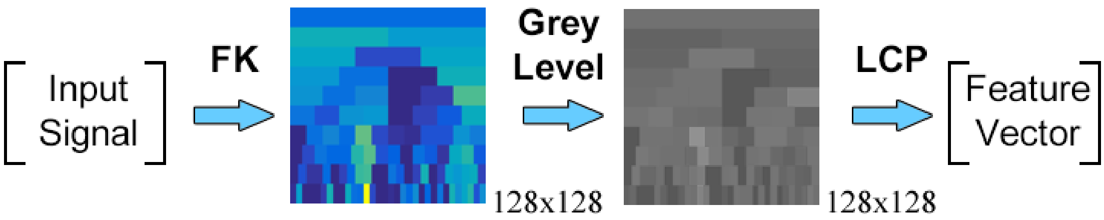
2.4 Histogram-Enhanced LBP-Kurtograms

Kurtogram approach can be considered as a cutting-edge diagnosis tool in condition monitoring. This technique is based on spectral kurtosis that had been long before proposed in the literature [11], providing a further and faster way of transforming the signal into frequency-delta frequency spectrum. One of the proposed algorithm in this paper is so called Fast Kurtogram (FK) [12]; divides the signal in low and high frequency bands as STFT does but with a different order to emphasize where spectral kurtosis is maximum by grid view in frequency-delta frequency domain which is claimed to be a few thousand times faster than spectral kurtosis.

Local Binary Patterns (LBP) [13], maximizes the mutual information by labeling the intensities of a 2D signal by thresholding the 3 x 3 neighborhood of each pixel intensity with the center pixel intensity and evaluates the result as a binary number. Local Configuration Pattern (LCP) is a descriptor that provides local information and circularly shifted histogram of pattern occurrences which make a 2D signal rotationally invariant [14]. LCP features represent both the microscopic features and local features represented by pattern occurrences. It may be considered as a special and rotationally invariant extension of the generalized method in pattern recognition, LBP.

Histogram Equalization (HE) [15] is an efficient technique to normalize pixel values according to the distribution frequencies of each intensity level which is a very fundamental way of enhancement for 2D signals.

Using three algorithms in a cascaded way yields to the proposed novel algorithm, so called Histogram Enhanced LBP-Kurtogram which is illustrated in Fig. 4.



Source: Author

Fig. 4 – Feature extraction process of Enhanced LBP-Kurtograms

3. EXPERIMENTAL ANALYSIS

Three different methods are used for feature extraction of the created two-class database. Statistical features (STATS) mean, standard deviation, median, mode, minimum and maximum are extracted and concatenated to achieve 1x6 feature vectors. These vectors, which maintain short size and provides computational efficiency, are used to train classifier with cross-validation. WPE features are created both in three level (WPE_3) and five level (WPE_5). LCP of Kurtograms with (E-LBP-K) and without (LBP-K) histogram equalization are also performed for feature extraction. Classification performance may be seen in Tab. 1.

Tab. 1 – The average recognition accuracies with their standard deviation values obtained by 6-fold cross validation

FLDA	**% Classification Success**				
Test Data	**LBP-K**	**STATS**	**E-LBP-K**	**WPE_3**	**WPE_5**
1-10	70	45	65	50	70
11-20	75	50	75	50	80
21-30	75	50	70	50	85
31-40	65	80	90	85	80
41-50	65	100	80	100	55
51-60	90	95	75	90	45
Average	73,3	70,0	**75,8**	70,8	69,2
Std. Dev.	9,3	24,7	**8,6**	23,3	15,9

Source: Author

According to the results in Tab. 1, it may be seen that both LBP-K and E-LBP-K methods are clearly better than classifying our two-class database.

CONCLUSION

In this research, a two class classification of empirically created database in consistence of signals both an accelerometer for vibration monitoring and a microphone. Using these two differently characterized outputs, a combined feature extraction attempt is carried out with five different ways. The proposed method in the title Enhanced Local Binary Pattern based Kurtogram outperforms not only in average classification performance but also stability in the results, referring to the standard deviation after six-fold cross validation. It is also possible to say that using higher levels of Wavelet Packet Energy is not sufficient to characterize the signal in a better way without any additional or preprocessing phase. It is also remarkable that Kurtogram approach, especially when histogram equalization is used before the feature extraction process, may assumed to have as much information as other methods even a challenging database with combined sensor data is used. This study also indicates that there is a high correlation between an accelerometer sensor on the rail and a microphone in the same horizontal position, by means of frequencies, thus the data is managed to be classified more than half of test samples successfully. Future study may be carried out in order to confirm results by using individual sensor data abnormalities. Concurrently, proposed approach may be used to diagnose different types of faults when appropriate filtering is done according to the related fault modes.

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