Failure Diagnostics on Railway Turnout Systems Using Support Vector Machines

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ABSTRACT
Railway turnout systems are one of the most critical pieces of equipment in railway infrastructure. Early identification of failures in turnout systems is important to obtain increased availability and safety, and reduced operating & support cost. This paper aims to develop a method to identify 'drive-rod out-of-adjustment' failure mode, one of the most frequently observed failure modes. Support Vector Machine with Gaussian kernel is used for classification. In addition, results of feature selection with statistical t-test and feature reduction with principal component analysis are compared in the paper.

Keywords
Failure diagnostics, Support Vector Machine, Railway Turnout Systems

1. INTRODUCTION
Condition Based Maintenance (CBM), also called predictive maintenance, is the philosophy of monitoring health of a machine by analyzing various signals collected from different sensors in order to have the minimum maintenance and failure cost. Diagnostics is a fundamental component of CBM and is defined as the detection of failure and its status (i.e. health state).

Turnout systems are one of the most important electro-mechanical devices in railway infrastructure. Failure identification-diagnostics has been attracted researchers and industry in recent years. There are three main approaches to identify the failure of a system: feature-based, empirically-based and model-based methods. In feature based approach, special features are extracted to identify the failures [1]. Empirically-based approaches analyze the difference of collected signal from a fault-free sample to identify the failure [4], [5]. In model-based approaches, failure is identified by the deviation amount of the collected signal from a pre-defined model [2], [3]. Failure identification methods for turnout systems are summarized in [6].

This paper presents a diagnostics method for 'drive-rod out-of-adjustment' failure mode, one of the most frequently observed failure modes. Support Vector Machine with Gaussian kernel is used for classification. In addition, results of feature selection with statistical t-test and feature reduction with principal component analysis are compared in the paper.

Section II presents the railway turnout system. Section III discusses support vector machine briefly, and section IV gives experiments and results with real data collected from a turnout system. Section V concludes the paper.

2. RAILWAY TURNOUT SYSTEMS
Turnout Systems are one of the most important components of the railway infrastructure. It allows trains to change their tracks by moving switch blades before the train passes. A turnout system includes motor to start the movement, gear-box to transfer the movement to drive arms and drive arms to push back and forth switch blades, and the metal platforms on traverses called slide chairs.

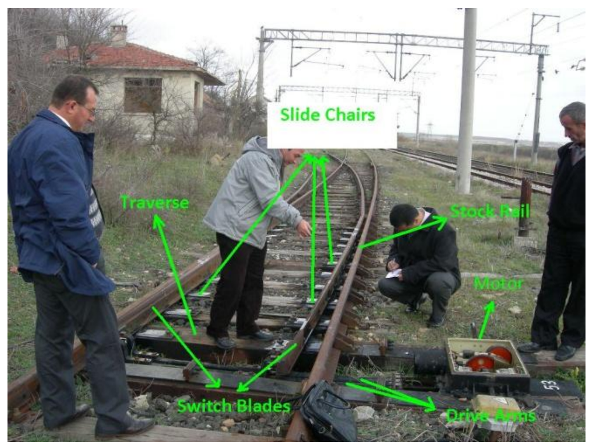

Figure 1. A turnout system located in Turkey

There are several types of turnout system such as electro-mechanic, pneumatic and hydraulic. In this study electro-mechanic type of turnout is used located in Babaeski/Tekirdağ.

3. SUPPORT VECTOR MACHINES
Support vector machine (SVMs) is a strong and famous classification method that has been used in various application areas. SVM works on the principal of margin maximization between classes [7]. Margin maximization is formulated as quadratic optimization problem. Solution of the quadratic optimization gives us the class of a given sample in the feature space.

Kernel methodology is an important aspect of SVM making the advantage of high dimensional space without really going to that

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space. Various kernel functions such as Gaussian and polynomial functions can be used. Readers are referred to [7], [8] for detailed information about SVM.

4. EXPERIMENTS & RESULTS

This section discusses five sub-modules: data collection, feature extraction, feature selection, feature reduction, and classification.

4.1 Data Collection

The system used for data collection is an electro-mechanical type turnout with two drive rods, one for each rail. A linear position measuring sensor is installed on stretchers of the turnout system and measures the linear position of the switch rails. Time series data are acquired from both normal to reverse and reverse to normal movements of a turnout system. Figs. 2 and 3 show the sensors and data acquisition systems, respectively.

Figure 2. Installed Sensors on Turnout System

Figure 3. Data Acquisition System

There are multiple failure modes in a turnout system. Goal of the study is to determine the level of "Drive Rod Out-of-adjustment" failure mode in a turnout system. The failure mode is obtained manually by loosening the bolts. Totally ten samples for fault-free and ten samples for failed states are available. When loosening of stretcher arm bolts failure modes occur, one can see the change in "Linear Ruler" sensory signal as illustrated in Fig. 4. Normal to reverse and reverse to normal data concatenated in the figure. Left part of the figure with downward lines represent backward (reverse to normal) movements, whereas right part with upward lines represents the forward (normal to reverse) movements. Fig. 4 displays the failure-free and failed (drive-rod-out-of-adjustment) samples together. It is clearly seen in the figure that there are two distinct line groups representing failure-free and failed samples in upward and downward lines. The difference in upward line is greater.

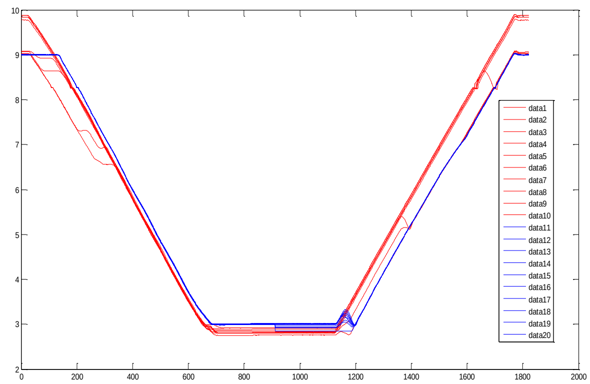
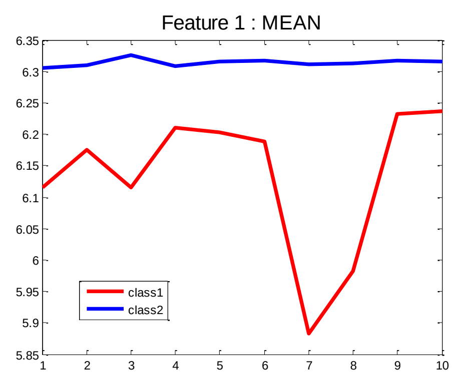
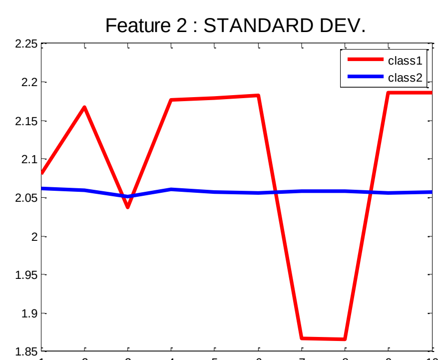


Figure 4. Linear Ruler sensor signals for all samples

4.2 Feature Extraction

Six features to be used for classification are mean (F1), standard deviation (F2), variance (F3), slope (F4), maximum (F5), and minimum (F6) of the signal obtained from linear ruler. Figure 5 displays the features of all samples for two classes (failure-free and failed). From these samples, we can observe if the samples are good enough to distinguish the classes. As seen from the figures, standard deviation and variance do not seem to be good features.





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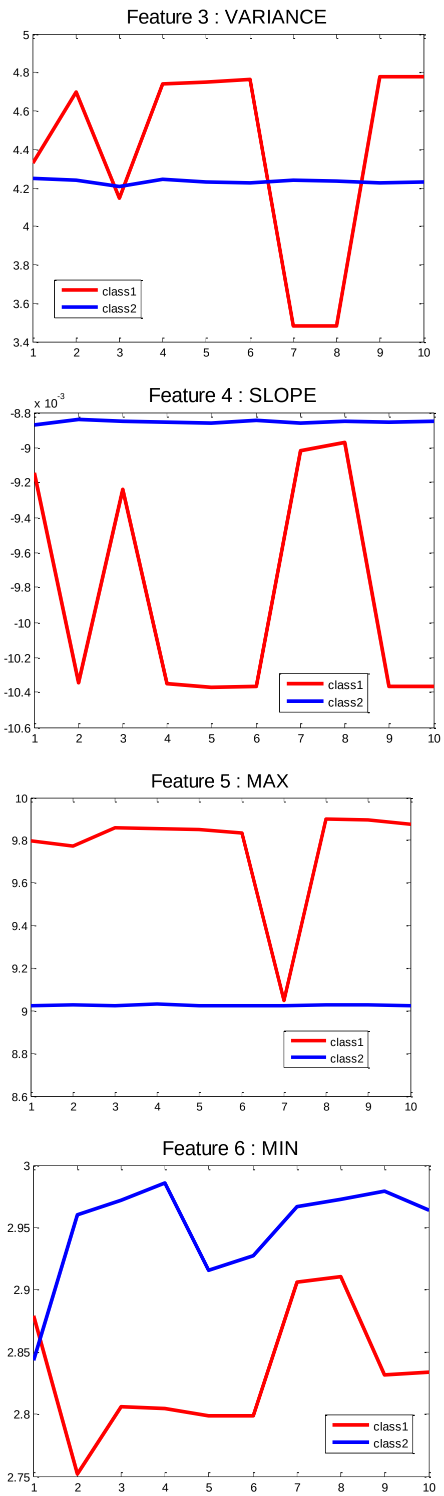

Figure 5. Extracted Features

4.3 Feature Selection

T-test is used to quantify the effectiveness of the features for classification. A null hypothesis about two classes having equal mean is analyzed. Table 1 displays the result of t-test analysis. Low p-value indicates that classes are distinguishable with the given feature. h = 0 indicates a failure to reject the null hypothesis at the 2.5% significance level. In this way features can be sorted from best to worst by p-values as f5 > f6 > f4 > f1 > f3 > f2. Thus the best two features F5 and F6 selected.

Table 1. p-values for all features

	F1	F2	F3
p-value	0,00013	0,4003208	0,3439391
h-value	1	0	0
	F4	**F5**	**F6**
p-value	0,00014	3,43E-08	3,37E-05
h-value	1	1	1

4.4 Feature Reduction

In this sub-module, feature reduction method, Principal Component Analysis (PCA) is employed. PCA transforms the existing features into new features by linear transformation. The new features are ranked by their representation ability to the variance of dataset. A given number of features with the highest representation ability are selected for classification. Readers are referred to [9] for details of PCA. Table 2 displays the transformation matrix used in PCA. Fig. 6 illustrates the direction of new features on two components.

Table 1. Linear Transformation Matrix

Transfromation Matrix					
0,0293	0,343132	0,809	0,476	0,023	0,000681
-0,144	0,181773	-0,031	-0,02	-0,966	0,105943
-0,6	0,721554	-0,194	-0,16	0,233	-0,02727
0,0013	-8,64E-05	0,003	0,001	-0,109	-0,994
-0,776	-0,57166	0,266	0,007	-4,00E-04	-8,83E-05
0,1277	0,042282	0,486	-0,86	-0,006	0,001135

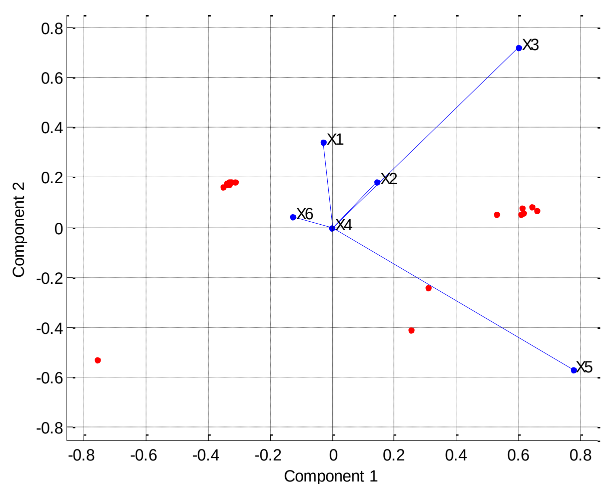

Figure 6. Uncorrelated new features obtained using PCA

Generated for PCA and used in classification; first two of these features (X1 and X2) cover the 98.6% of the total variance as

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could be seen from Figure 6. Note that X1 and X2 are the features obtained using PCA and are linear combination of existing features mentioned section 2.2. Linear transformation matrix used to obtain new uncorrelated features is shown in Table 2.

4.5 Classification

70 % of data used to train SVM, the rest is used for testing. SVM classification method with Gaussian kernel is used to classify data both after feature selection and feature reduction. As seen from the Fig. 7, one misclassified data exists in the result with feature selection approach. Fig. 8 shows the classification result with feature reduction with PCA. Classes in the figures represent the 'failure-free' and 'failed' states of the turnout systems.

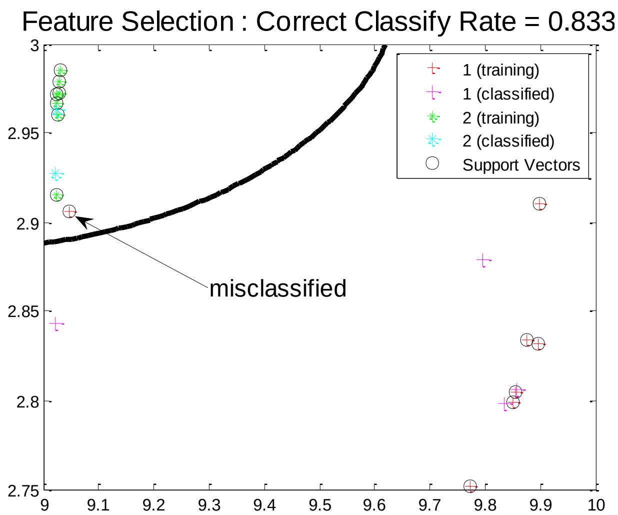

Figure 7. Feature Selection classification results

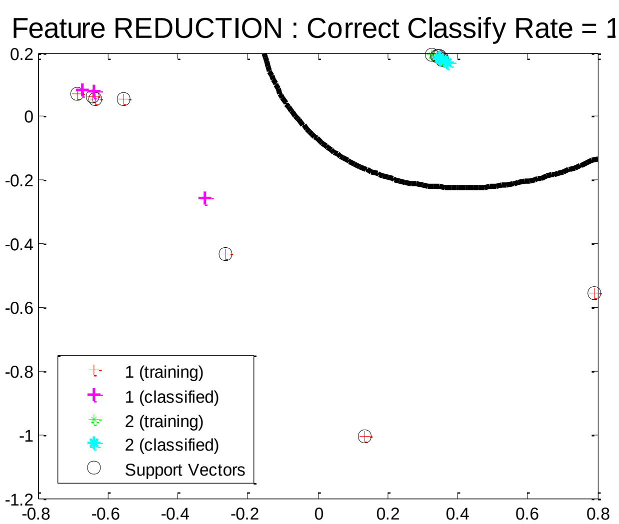

Figure 8. Feature Reduction results

Classification accuracy results are shown in Table 3. As seen from the table, results with feature reduction are better than results with feature selection. Thus, even some of the feature seems to be not efficient enough, they may carry some value in classification, which can be incorporated in the new features obtained in PCA.

Table 1. Classification accuracy comparison

	Feature Selection	Feature Reduction
Accuracy	83.3%	100%

5. CONCLUSION

Railway turnout systems are one of the most critical components of railway structures. It is critical to identify failures in railway turnouts. This paper presents a SVM based failure identification method. Drive-rod-out-of-adjustment failure mode is selected for experiment. The failure is obtained manually. Collected data is analyzed with feature selection and reduction with PCA. Then, SVM is used for classification. Classification using the features obtained with PCA gives better results than only selecting the existing features.

6. ACKNOWLEDGMENTS

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