

Condition Monitoring of Elevator Systems using Deep Neural Network

Krishna Mohan Mishra and Kalevi Huhtala

Unit of Automation Technology and Mechanical Engineering, Tampere University, Tampere, Finland

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Abstract: In this research, we propose a generic deep autoencoder model for automatic calculation of highly informative deep features from the elevator data. Random forest algorithm is used for fault detection based on extracted deep features. Maintenance actions recorded are used to label the sensor data into healthy or faulty. In our research, we have included all fault types present for each elevator. The rest of the healthy data is used for validation of the model to prove its efficacy in terms of avoiding false positives. New extracted deep features provide 100% accuracy in fault detection along with avoiding false positives, which is better than statistical features. Random forest was also used to detect faults based on statistical features to compare results. New deep features extracted from the dataset with deep autoencoder random forest outperform the statistical features. Good classification and robustness against overfitting are key characteristics of our model. This research will help to reduce unnecessary visits of service technicians to installation sites by detecting false alarms in various predictive maintenance systems.

1 INTRODUCTION

In recent years, apartments, commercial facilities and office buildings are using elevator systems more extensively. Nowadays, urban areas comprised of 54% of the worlds population (Desa, 2014). Therefore, proper maintenance and safety are required by elevator systems. Development of predictive and preemptive maintenance strategies will be the next step for improving the safety of elevator systems, which will also increase the lifetime and reduce repair costs whilst maximizing the uptime of the system (Ebeling, 2011), (Ebeling and Haul, 2016). Predictive maintenance policy are now being opted by elevator production and service companies for providing better service to customers. They are estimating the remaining lifetime of the components responsible for faults and remotely monitoring faults in elevators. Fault detection and diagnosis are required by elevator systems for healthy operation (Wang et al., 2009).

State of the art include fault diagnosis methods having feature extraction methodologies based on deep neural networks (Zhang et al., 2017), (Jia et al., 2016), (Bulla et al., 2018) and convolutional neural networks (Xia et al., 2018), (Jing et al., 2017) for rotatory machines similar to elevator systems. Fault detection methods for rotatory machines are also using support vector machines (Martínez-Rego et al., 2011) and extreme learning machines (Yang and Zhang,

2016). However, to improve the performance of traditional fault diagnosis methods, we have developed an intelligent deep autoencoder model for feature extraction from the data and random forest performs the fault detection in elevator systems based on extracted features.

In the last decade, highly meaningful statistical patterns have been extracted with neural networks (Calimeri et al., 2018) from large-scale and high-dimensional datasets. Elevator ride comfort has also been improved via speed profile design using neural networks (Seppala et al., 1998). Nonlinear time series modeling (Lee, 2014) is one of the successful application of neural networks. Relevant features can be self-learned from multiple signals using a deep learning network (Fernández-Varela et al., 2018). Deep learning algorithms are frequently used in areas such as preventive maintenance (Arima et al., 2012), decision support system (Sedlak et al., 2013), fraud detection (Mendes et al., 2012), forecasting (Ferhatosmanoglu and Macit, 2016) and text classification (Wang and Choi, 2012). Autoencoding is a process based on feedforward neural network (Hänninen and Kärkkäinen, 2016) for nonlinear dimension reduction with natural transformation architecture. Autoencoders (Albuquerque et al., 2018) are very powerful as nonlinear feature extractors. Autoencoders can extract features of high interest from sensor data for

increasing the generalization ability of machine learning models (Huet et al., 2016). Autoencoders have been studied for decades and were first introduced by LeCun (Fogelman-Soulie et al., 1987). Traditionally, autoencoders have two main features i.e. feature learning and dimensionality reduction. Autoencoders and latent variable models (Madani and Vlajic, 2018) are theoretically related, which promotes them to be considered as one of the most compelling subspace analysis techniques. Feature extraction method based on autoencoders are used in systems like induction motor (Sun et al., 2016) and wind turbines (Jiang et al., 2018) for fault detection, different from elevator systems as in our research.

In our previous research, elevator key performance and ride quality features were calculated from mainly acceleration signals of raw sensor data, which we call here statistical features. Random forest has classified these statistical features to detect faults. Expert knowledge of the domain is required to calculate statistical domain specific features from raw sensor data but there will be loss of information to some extent. To avoid these implications, we have developed a deep autoencoder random forest approach for automated feature extraction from elevator sensor data, and based on these deep features, faults are detected. The rest of this paper is organized as follows. Section 2 presents the methodology of the paper including deep autoencoder and random forest algorithms. Then, section 3 includes the details of experiments performed, results and discussion. Finally, section 4 concludes the paper and presents the future work.

2 METHODOLOGY

In this research, we have used 12 different statistical features describing the motion and vibration of an elevator. These features are derived from raw sensor data for fault detection and diagnostics of multiple faults. We have developed an automatic feature extraction technique in this research as an extension to the work of our previous research (Mishra et al., 2019) to compare the results using new extracted deep features. We have analyzed almost nine months of the data from three traction elevators in this research as an extension to the work of our previous research. Each elevator produces around 200 rides per day. Data collected from an elevator system is fed to the deep autoencoder model for new feature extraction and then random forest performs the fault detection task based on extracted deep features. We have used 70% of the data for training and rest 30% for testing. Figure 1 shows the fault detection approach used in this pa-

per, which includes elevator data extracted based on time periods provided by the maintenance data. Data collected from elevator systems is fed to the deep autoencoder model for feature extraction and then random forest performs the fault detection task based on extracted deep features.

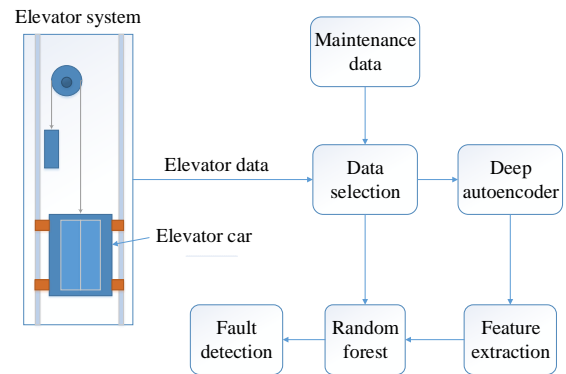


Figure 1: Fault detection approach.

2.1 Deep Autoencoder

We have developed a deep autoencoder model based on deep learning autoencoder feature extraction methodology. A basic autoencoder is built on feed-forward neural network with a fully connected three-layer network including one hidden layer. Input and output layer of a typical autoencoder have same number of neurons and reproduces output as its inputs. We are using a five layer deep autoencoder (see Figure 2) including input, output, encoder, decoder and representation layers, which is a different approach than in (Jiang et al., 2018), (Vincent et al., 2008). Every movement of the elevator generates statistical features from the vibration signal. In our approach, we first feed the elevator data from each elevator movement in up and down directions separately in the deep autoencoder model to extract new deep features from the data. Then we apply random forest as a classifier for fault detection based on new deep features extracted from the data.

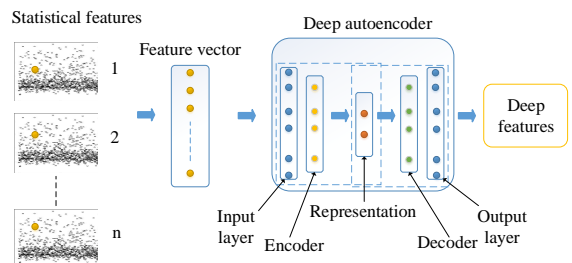


Figure 2: Deep autoencoder feature extraction approach.

The encoder transforms the input x into corrupted input data x' using hidden representation h through nonlinear mapping

$$h = f(W_1 x' + b) \quad (1)$$

where $f(\cdot)$ is a nonlinear activation function as the sigmoid function, $W_1 \in \mathbb{R}^{k \times m}$ is the weight matrix and $b \in \mathbb{R}^k$ the bias vector to be optimized in encoding with k nodes in the hidden layer (Vincent et al., 2008). Then, with parameters $W_2 \in \mathbb{R}^{m \times k}$ and $c \in \mathbb{R}^m$, the decoder uses nonlinear transformation to map hidden representation h to a reconstructed vector x'' at the output layer.

$$x'' = g(W_2 h + c) \quad (2)$$

where $g(\cdot)$ is again nonlinear function (sigmoid function). In this study, the weight matrix is $W_2 = W_1^T$, which is tied weights for better learning performance (Japkowicz et al., 2000).

2.2 Random Forest

Random forest is type of ensemble classifier selecting a subset of training samples and variables randomly to produce multiple decision trees (Breiman, 2001). High data dimensionality and multicollinearity can be handled by a RF classifier while imbalanced data affect the results of the RF classifier. It can also be used for sample proximity analysis, i.e. outlier detection and removal in train set (Belgiu and Drăguț, 2016). The final classification accuracy of RF is calculated by averaging the probabilities of assigning classes related to all produced trees (t). Testing data (d) that is unknown to all the decision trees is used for evaluation by voting method. Selection of the class is based on the maximum number of votes (see Figure 3). Random forest classifier provides variable importance measurement that helps in reducing the dimensions of hyperspectral data in order to identify the most relevant features of data, and helps in selecting the most suitable reason for classification of a certain target class.

Specifically, let sensor data value v_l^t have training sample l^{th} in the arrived leaf node of the decision tree $t \in T$, where $l \in [1, \dots, L_t]$ and the number of training samples is L_t in the current arrived leaf node of decision tree t . The final prediction result is given by (Huynh et al., 2016):

$$\mu = \frac{\sum_{t \in T} \sum_{l \in [1, \dots, L_t]} v_l^t}{\sum_{t \in T} L_t} \quad (3)$$

All classification trees providing a final decision by voting method are given by (Liu et al., 2017):

$$H(a) = \arg \max_{y_j} \sum_{i \in [1, 2, \dots, Z]} I(h_i(a) = y_j) \quad (4)$$

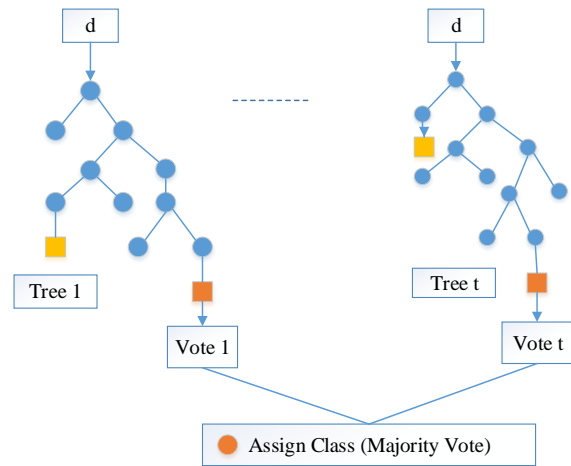


Figure 3: Classification phase of random forest classifier.

where $j = 1, 2, \dots, C$ and the combination model is $H(a)$, the number of training subsets are Z depending on which decision tree model is $h_i(a)$, $i \in [1, 2, \dots, Z]$ while output or labels of the P classes are y_j , $j = 1, 2, \dots, P$ and combined strategy is $I(\cdot)$ defined as:

$$I(x) = \begin{cases} 1, & h_i(a) = y_j \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

where output of the decision tree is $h_i(a)$ and i^{th} class label of the P classes is y_j , $j = 1, 2, \dots, P$.

2.3 Evaluation Parameters

Evaluation parameters used in this research are defined with the confusion matrix in Table 1.

Table 1: Confusion matrix.

	Predicted (P)	(N)
Actual (P)	True positive (TP)	False negative (FN)
(N)	False positive (FP)	True negative (TN)

The rate of positive test result is sensitivity,

$$Sensitivity = \frac{TP}{TP + FN} * 100\% \quad (6)$$

The ratio of a negative test result is specificity,

$$Specificity = \frac{TN}{TN + FP} * 100\% \quad (7)$$

The overall measure is accuracy,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} * 100\% \quad (8)$$

3 RESULTS AND DISCUSSION

In this research, we have included all three elevators E001, E002, E003 and their combined version (All) similar to our previous research. First, we selected the faulty data based on time periods provided by the maintenance data. In the next step, an equal amount of healthy data was also selected and labelled as class 0 for healthy, with class 1 for faulty data. Finally, the deep autoencoder model is used for feature extraction from the data.

3.1 Up Movement

We have analyzed up and down movements separately because the traction based elevator usually produces slightly different levels of vibration in each direction. Healthy and faulty data with class labels are fed to the deep autoencoder model and the generated deep features are shown in Figure 4. In Figure 4, we can see that both features with class labels are perfectly separated, which results in better fault detection. These are called deep features or latent features in deep autoencoder terminology, which shows hidden representations of the data.

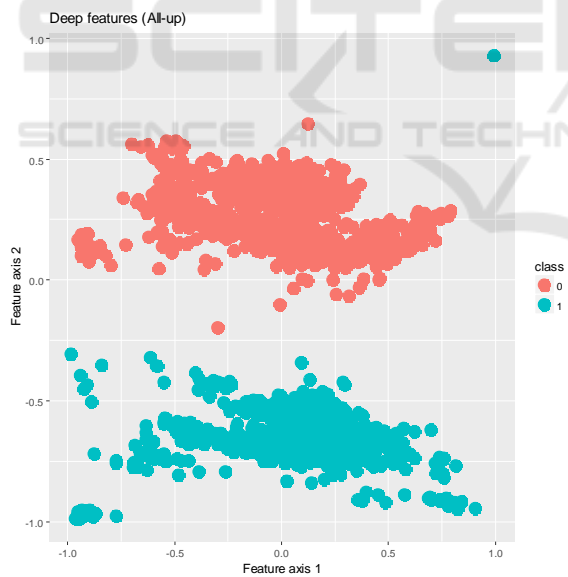


Figure 4: Extracted deep autoencoder features for combined version (All) (Visualization of the features w.r.t class variable).

The extracted deep features are fed to the random forest algorithm for classification and the results provide 100% accuracy in fault detection, as shown in Table 2. We have also calculated accuracy in terms of avoiding false positives from both features and found that the new deep features generated in this research

outperform the statistical features. We have used the rest of the healthy data to analyze the number of false positives. This healthy data is labelled as class 0 and fed to the deep autoencoder to extract new deep features from the data, as presented in Figure 5. These new deep features are then classified with the pre-trained deep autoencoder random forest model to test the efficacy of the model in terms of false positives.

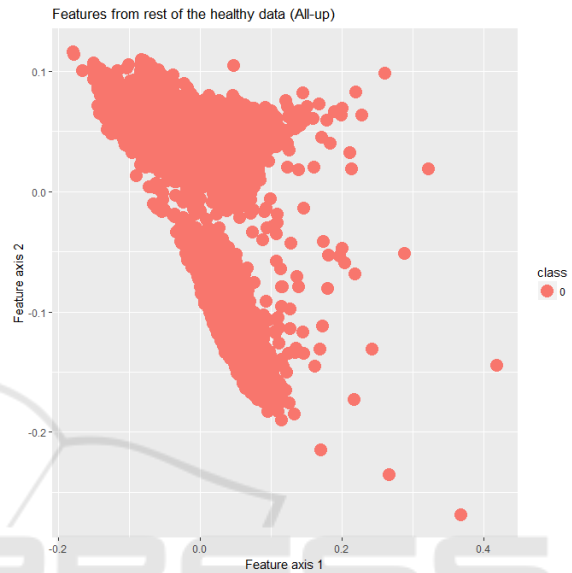


Figure 5: Extracted deep features (only healthy data) for combined version (All).

Table 2 presents the results for upward movement of the elevator in terms of accuracy, sensitivity and specificity. We have also included the accuracy of avoiding false positives as evaluation parameters for this research. The results show that the new deep features provide better accuracy in terms of fault detection and avoiding false positives from the data, which is helpful in detecting false alarms for elevator predictive maintenance strategies. It is extremely helpful in reducing the unnecessary visits of maintenance personnel to installation sites.

Table 2: Fault detection analysis (False positives field related to analyzing rest of the healthy data after the training and testing phase).

	Deep features	Statistical features
Accuracy	1	0.78
Sensitivity	1	0.78
Specificity	1	0.78
False positives	1	0.94

3.2 Down Movement

For downward motion, just as in the case of up move-

ment, we feed both healthy and faulty data with class labels to the deep autoencoder model for the extraction of new deep features, as shown in Figure 6.

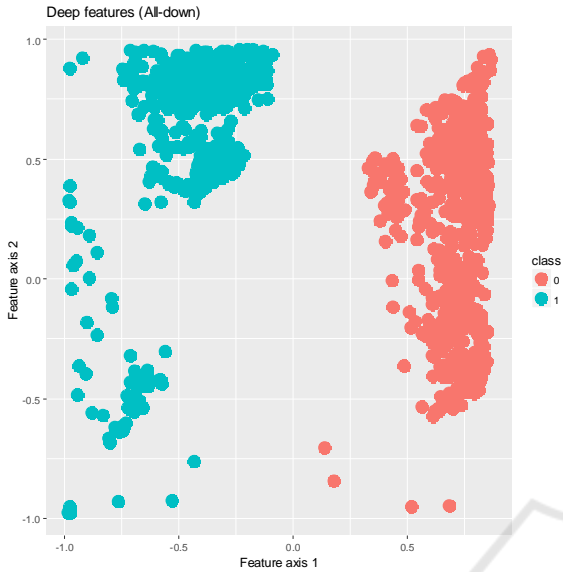


Figure 6: Extracted deep features for combined version (All).

Finally, the new extracted deep features are classified with random forest model, and the results are shown in Table 3. After this, the rest of the healthy data with class label 0 is used to analyze the number of false positives. The extracted deep features are presented in Figure 7. Table 3 presents the results for fault detection with deep autoencoder random forest model in the downward direction. The results are similar to the upward direction, but we can see significant change in terms of accuracy when analyzing the fault detection and number of false positives with new deep features.

Table 3: Fault detection analysis.

	Deep features	Statistical features
Accuracy	1	0.74
Sensitivity	1	0.78
Specificity	1	0.70
False positives	1	0.89

4 CONCLUSIONS AND FUTURE WORK

In this research, we propose a novel fault detection technique for health monitoring of elevator systems. We have developed a generic model for automated feature extraction and fault detection in the health state monitoring of elevator systems. Our approach

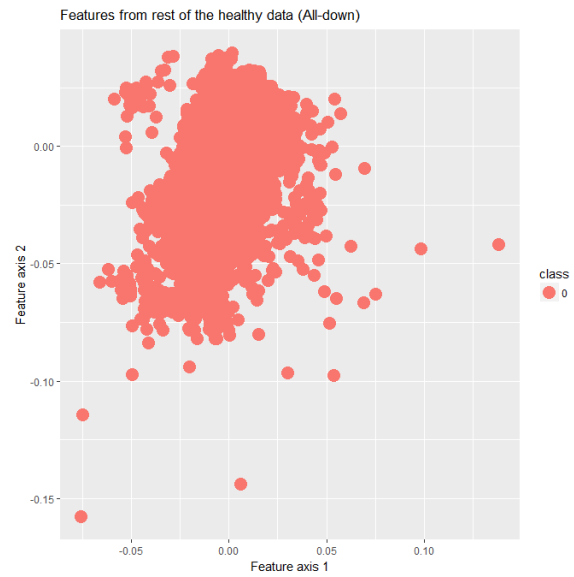


Figure 7: Extracted deep features (only healthy data) for combined version (All).

with new extracted deep features provided 100% accuracy in detecting faults and in avoiding false positives. The results show that we have succeeded in developing a generic model, which can also be applicable to other machine systems for automated feature extraction and fault detection. The results are useful in terms of detecting false alarms in elevator predictive maintenance. If the analysis results are utilized to allocate maintenance resources, the approach will also reduce unnecessary visits of maintenance personnel to installation sites. Our developed model can also be used for solving diagnostics problems with automatically generated highly informative deep features in different predictive maintenance solutions. Our model outperforms because of new deep features extracted from the dataset as compared to statistical features calculated from the raw sensor dataset of the same elevators. No prior domain knowledge is required for the automated feature extraction approach. Robustness against overfitting and dimensionality reduction are the two main characteristics of our model. Our generic model is feasible as shown by the experimental results, which will increase the safety of passengers. Robustness of our model is tested in the case of a large dataset, which proves the efficacy of our model.

In future work, we will extend our approach on more elevators and real-world big data cases to validate its potential for other applications and improve its efficacy.

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