Vibration Signature and the Application of Intelligent Pattern Recognition in Detection and Classification of Damage in Automatic Power Operated Lift Doors

S. Kaczmarczyk, R. Smith, Mateusz Gizicki

Faculty of Arts, Science and Technology, The University of Northampton, UK

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Abstract. The majority of faults in lift installations occur in the door (entrance) systems. Wear and tear of the door operator mechanism and the door system components/ subsystems will result in defects that lead to damage which in turn leads to faults, understood as a change in the door system that produces an unacceptable reduction in the quality of its performance. The research presented in this paper involved the development of an experimental lift door stand to collect vibration signature datasets corresponding to a range of typical damage classes that occur in lift door systems. The installation comprises single speed doors (single panel side opening and two panel centre opening) as well as two speed doors (two panel side opening and four panel centre opening). Once the data are collected the vibration features are extracted and used in supervised learning to train the artificial neural networks designed to recognize patterns and to classify damage. The results obtained demonstrate excellent performance of the network with very high percentage of correctly classified damage classes involved. The work completed so far forms the basis for the development of decision stage algorithms to analyze the results from the pattern recognition and to decide about appropriate maintenance actions required.

1 INTRODUCTION

Fault data collected from lift installation sites show that the majority of faults occur in door (entrance) systems [1]. The lift entrance system comprises landing (hoistway) doors and car doors. Most elevators intended for passengers have fully automated power-operated doors. The standard arrangement for automatic power operation involves a 'master' operator, a self-contained electric motor driven unit mounted on the car top. The unit is coupled mechanically with the car door through a linkage system, a toothed belt or similar device to achieve the speed profile for opening and closing of the doors. The door motion is electronically controlled. A block diagram of an electronically controlled door operator is shown Fig. 1 [2]. In this arrangement the microprocessor unit senses the position of the doors (usually via a simple optical encoder mounted on the motor, as shown), and controls the speed of the motor in accordance with the position of the doors, as required by an inbuilt speed/position profile held in the microprocessor memory. The doors can operate at different speeds under different circumstances.

Wear and tear of the door operator mechanism and the door system components/ subsystems will result in damage and the system is no longer operating in its ideal condition (but can still function satisfactorily). This in turn will lead to a fault, when the system can no longer operate satisfactorily (a change that produces an unacceptable reduction in quality) [3].

There should be a relevant maintenance strategy in place for planning and implementing repairs or replacements of damaged/ faulty components/ subsystems in lift systems [4]. The preferred strategy is predictive maintenance where the condition is monitored (while the system is operating) and any damage is detected and identified very early before the fault is developed. The condition monitoring then predicts when maintenance should be performed.

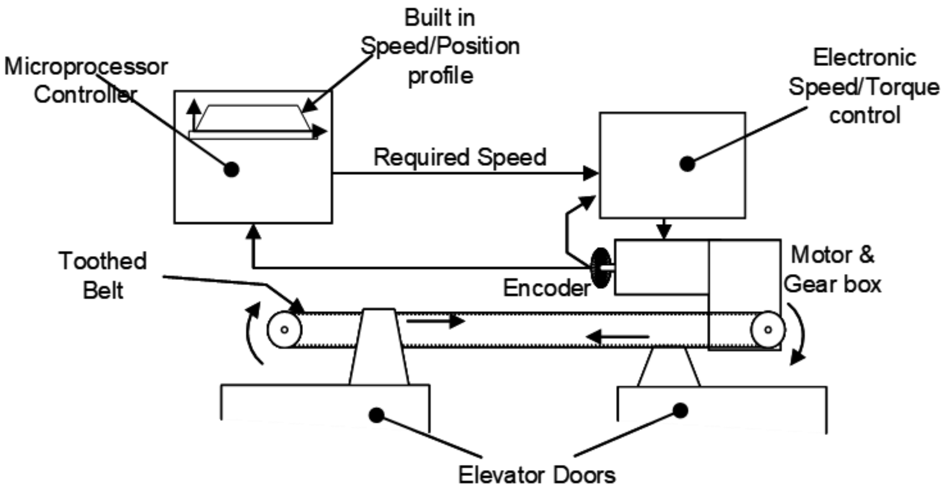


Figure 1 Automated power-operated door: an electronically controlled door operator

Bearing this in mind, the following hierarchical structure and the method levels in damage identification should be followed [3]:

1. Detection: the method gives a qualitative indication that damage might be present in the system.
2. Localisation: the method gives information about the probable position of the damage.
3. Classification: the method gives information about the type of damage.
4. Assessment: the method gives an estimate of the extent of the damage.
5. Prediction: the method offers information about the safety of the system, and possibly estimates a residual life.

In this paper the application of machine learning (ML) techniques and Artificial Neural Networks (ANN) algorithm based on vibration signal data for damage detection and classification in lift door systems is investigated. An experimental test rig to generate a comprehensive set of vibration test data corresponding to a range of typical damage classes that occur in lift door systems has been developed. Once the data are collected, suitable vibration features are extracted and used in supervised learning to train the ANN designed to recognize patterns and to classify damage.

2 EXPERIMENTAL SETUP AND VIBRATION DATA

The experimental lift door stand to carry out tests and collect vibration data has been developed. The stand has been designed to accommodate various types of lift doors: single speed doors (single panel side opening and two panel centre opening) as well as two speed doors (two panel side opening and four panel centre opening). Fig. 2(a) shows two speed two panel side opening doors fitted in the stand frame. The door motion and vibrations have been monitored by using B&K accelerometer sensors (see Fig. 2(b)) attached to the door structure at various locations. The analogue signals from the accelerometers are recorded by using the B&K LAN-XI recorder platform. Three LAN-XI modules (see Fig. 2(c)) with four input channels each are applied.

The door speed / acceleration and jerk are monitored during/ jerk profiles are determined by integrating / differentiating the acceleration signals obtained from sensors mounted on the car and hoistway door sets, respectively (see Fig. 3). The time records of vibration responses are postprocessed and then used in supervised learning to train the ANN, designed to recognize patterns and to classify damage. The raw time data sets are pre-processed and normalized (see Figure 4(a)). These are post-processed to develop spectrograms (see Fig. 4(b)). The cepstrogram (see Fig. 4 (c)) is then calculated to extract its real coefficients as features to be used in the neural network pattern recognition (NNPR) algorithm.

(a)

(b)

(c)

Figure 2 Experimental setup

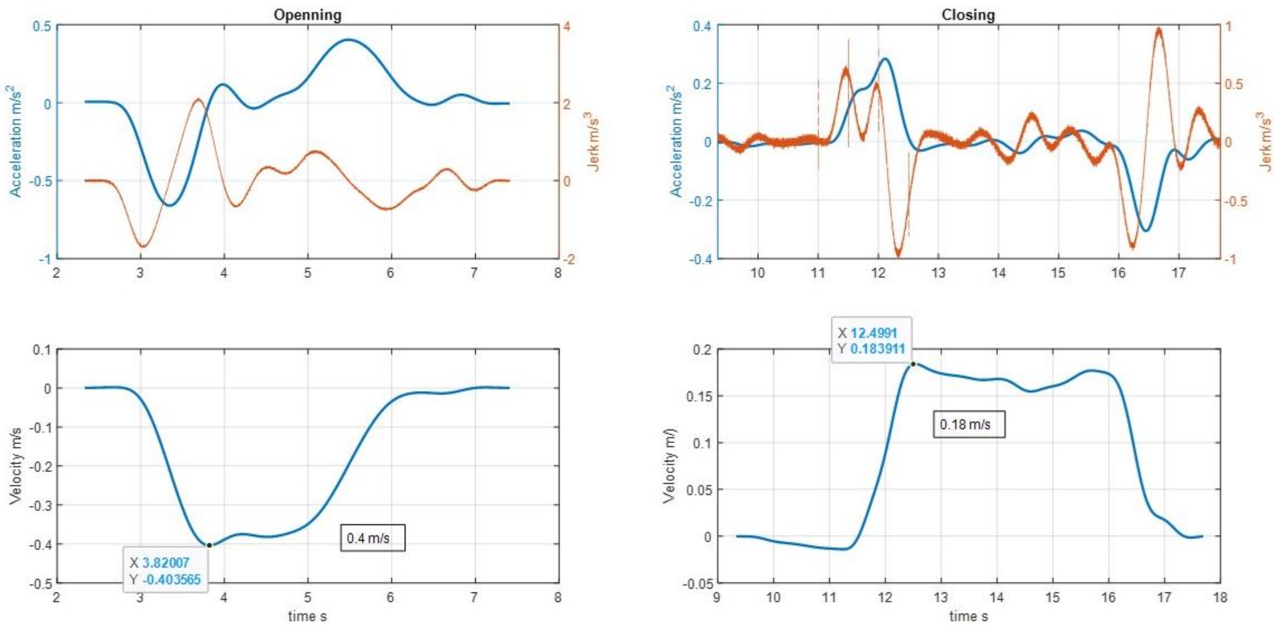


Figure 3 Door motion jerk / acceleration and speed time profiles

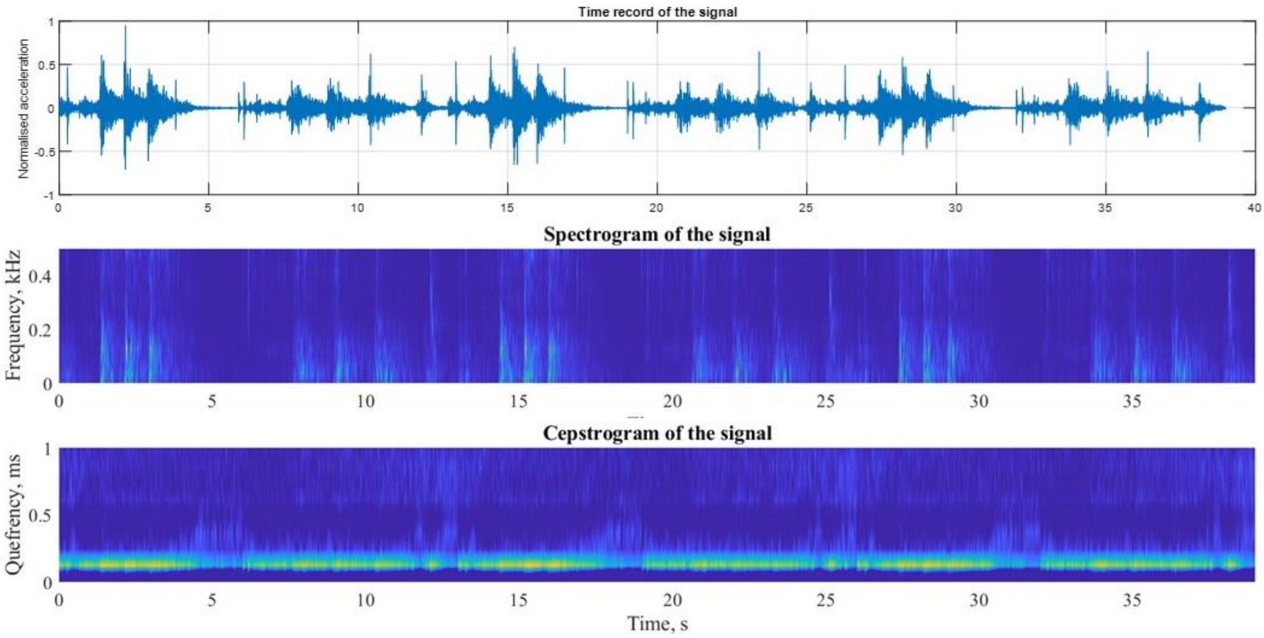


Figure 4 Single panel side opening door vibration data: (a) normalized acceleration signal, (b) spectrogram, (c) cepstrogram

3 DAMAGE PATTERN RECOGNITION BY USING ARTIFICIAL NEURAL NETWORK ALGORITHM

Eight main categories of ‘damage’ are considered (and are referred to as ‘damage classes’). These are as listed in Table 1.

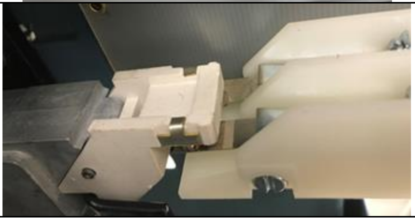
Supervised machine learning is applied to develop a NNPR algorithm to classify the damage. In the algorithm an input data set (based on the cepstrogram features) is classified into a set of target categories (the target dataset comprises vectors with a sequence of 0, 1 elements, see Table 1). The algorithm needs to have prior knowledge and it is necessary to construct examples of data corresponding to each damage class. Thus, a *training set* of data/measurements vectors associated uniquely with each class is necessary. Consider an example in which a shallow neural network is used. The network is developed by using the MATLAB ‘nprtool’ app [5]. The network is a two-layer feed-forward network (see Fig. 5(a)).

Fig. 5(b) shows the confusion matrix from testing after the training. This matrix demonstrates the following:

- the rows correspond to the predicted (output) class,
- the columns correspond to the true (target) class,
- the diagonal cells correspond to samples that are correctly classified,
- the off-diagonal cells correspond to incorrectly classified samples,
- the column on the far right shows the percentages of all the examples predicted to belong to each class that are correctly classified (positive predictive values) and incorrectly classified (false discovery rates),
- the cell in the bottom right of the plot shows the overall accuracy.

The test confusion matrix indicates the classification performance. The overall accuracy is 97.9% which demonstrates excellent performance of the NNPR algorithm.

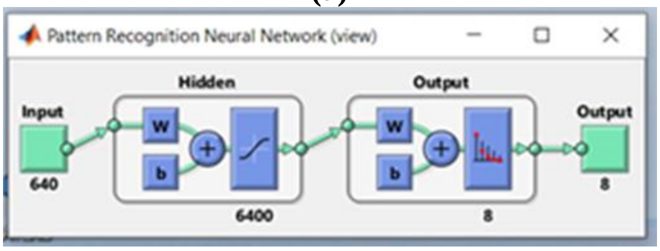
Table 1 Damage Classes

Class No.	Description / target vector	Deatails
1	**No damage** $[1\ 0\ 0\ 0\ 0\ 0\ 0\ 0]^T$	**Baseline state of the door installation**
2	**Car door roller with damage** $[0\ 1\ 0\ 0\ 0\ 0\ 0\ 0]^T$	
3	**Hoistway door roller with damage** $[0\ 0\ 1\ 0\ 0\ 0\ 0\ 0]^T$	
4	**Door panel sill guide contaminated** $[0\ 0\ 0\ 1\ 0\ 0\ 0\ 0]^T$	
5	**Damaged interlock rollers** $[0\ 0\ 0\ 0\ 1\ 0\ 0\ 0]^T$	
6	**Low tensioned (loose) door drive belt** $[0\ 0\ 0\ 0\ 0\ 1\ 0\ 0]^T$	
7	**Damaged belt tooth** $[0\ 0\ 0\ 0\ 0\ 0\ 1\ 0]^T$	
8	**Interlock misalignment** $[0\ 0\ 0\ 0\ 0\ 0\ 0\ 1]^T$	

4 CONCLUSIONS

The results obtained demonstrate excellent performance of the network with a very high percentage of correctly classified damage classes investigated. The work completed so far forms the basis for further work. This will involve the development of decision stage algorithms to analyze the results from the pattern recognition and to decide about the appropriate maintenance actions required.

(a)



(b)

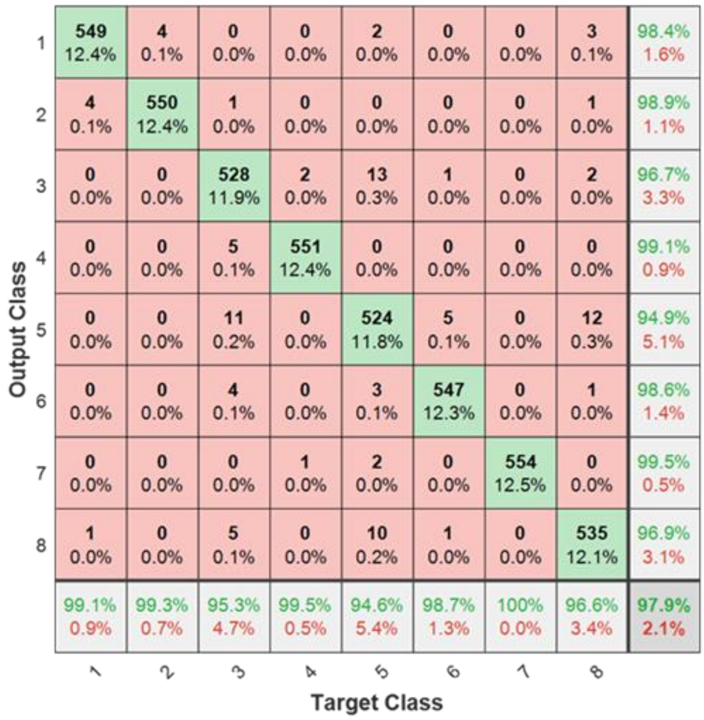


Figure 5 (a) neural network, (b) test confusion matrix

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BIOGRAPHICAL DETAILS

Dr Stefan Kaczmarczyk is Professor of Applied Mechanics and Postgraduate Programme Leader for Lift Engineering at the University of Northampton, UK. His expertise is in the area of applied dynamics and vibration with particular applications to vertical transportation and material handling systems. He has published over 100 journal and international conference papers in this field. He is a Chartered Engineer, elected Fellow of the Institution of Mechanical Engineers and a Fellow of the Higher Education Academy.

Dr Rory Smith has over 49 years of experience in all aspects of the lift industry including sales, installation, maintenance, manufacturing, engineering, research & development. He has worked for ThyssenKrupp Elevator for the last 23 years. Prior to becoming involved in ThyssenKrupp's Internet of Things, he was Operations Director, ThyssenKrupp Elevator Middle East. His scientific interests include: operations management, high rise - high speed technology, ride quality, traffic analysis, dispatching. To date he has been awarded numerous patents in these areas and has many pending patents.

Mateusz Gizicki is a postgraduate researcher at the University of Northampton. He has a bachelor's degree in Mechanical Engineering from the University of Northampton and is currently working towards achieving his doctorate in the area of Multi-Physics and Computational Fluid Dynamics. He is an Associate Member of the Institution of Mechanical Engineers and has experience in research and development in the industry environment as well as academia. In addition, he has recently completed the Knowledge Transfer Partnership project as a KTP Associate, which combined management skills with complete product development.