ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, Vol 9(S1), DOI: 10.17485/ijst/2016/v9i(S1)/109889 December 2016 ISSN (Online) : 0974-5645

Design and Implementation of Marine Elevator Safety Monitoring System based on Machine Learning

Young Wook Cho*[1], Jae Myoung Kim[2] and Yoon Yong Park[3]

[1]Department of Computer Engineering, SunMoon University, 70, Sunmoon-ro 221 Beon-gil, Tangjeong-myeon, Asan-si, Chungcheongnam-do, 31460, Rep. of Korea; ywcho@sunmoon.ac.kr
[2]Smart Mobility Research Department, ETRI, 218, Gajeong-ro, Yuseong-gu, Daejeon, 34129, Rep. of Korea; jaemkim@etri.re.kr
[3]Department of Computer Engineering, SunMoon University, 70, Sunmoon-ro 221 Beon-gil, Tangjeong-myeon, Asan-si, Chungcheongnam-do, 31460, Rep. of Korea; yypark@sunmoon.ac.kr

Abstract

Objectives: Marine elevators require the mechanism of safety management due to the difficulty of their maintenance in voyage. It is necessary to monitor the status of elevators using sensors and to provide the maintenance information locally and remotely. **Methods/Statistical Analysis:** We designed and implemented a safety elevator monitoring system based on the NMEA 2000 network, which implements maintenance prediction in the gateway using big data on the server. **Findings:** We conducted supervised learning using labeled data, which are results of event messages from In-network processing module of logging gateway. The accuracy of load and platform tilt based slope prediction model is 0.99 or above, but the accuracy of roll and pitch based slope prediction model is below 0.94. Therefore, it cannot be adapted to the logging gateway prediction model. Features for prediction models have a very important role in accuracy of results during experimenting and we can use highly accurate prediction models in logging gateway to analyze the sensor data. **Improvements/Applications:** In the decision accuracy of operating condition, 0.95 or above accuracy is obtained using an operating time feature having the ±1 second margin. But for more high accuracy, we need experts' analysis to modify the prediction model. This system can automate the decision of elevator problems using sensor monitoring and diagnosis prediction model.

Keywords: Diagnosis Prediction, Elevator Safety Maintenance, Logging Gateway, Marine Elevator, Sensor Monitoring

1. Introduction

With recent advancements, elevator controllers have various sensors to monitor the status of operating elevators for preventive maintenance. These elevator monitoring system designs can monitor the running status of the elevator and ensure the safety of the elevator. Marine elevators especially need the safety and maintenance monitoring capabilities due to the difficulty of maintenance at sea. An elevator company is planning to attach a device that collects error codes and other data about the operation of the elevator and sends them to the monitoring platform, which then analyzes the data using machine learning[1,2].

As a result, they are expecting to enhance the maintenance ability. We developed the marine safety monitoring system based on NMEA 2000 controllers and logging gateway[3]. This system can handle the various sensor data and provide the diagnostic prediction information to the elevator controller. Adopted sensors include load cells, 9-axis IMU (Inertial Measurement Unit), wire rope clip, proximity, limit switch, etc. The logging gateway performs in-network sensor data processing because of the large volumes of raw data[4]. The gateway can control the elevator controllers using the algorithms generated from various prediction model. Features for the prediction model have a very important role in the decision-making process. In addition to the prediction model based on the

* Author for correspondence

big data on the server, subject matter experts' decisions are needed in the process[5].

2. System Design and Implementation

2.1 System Design

The stakeholders such as ship owners and maintenance enterprises require marine elevator safety monitoring systems, which are able to:

- Collect status of all elevator operations and safety components
- Monitor the safety and operating status of the elevator remotely
- Analyze the status of the elevator and diagnose the error status in voyage
- Report the status of the elevator for easy maintenance during the ship's arrival in port

Our monitoring system is designed to satisfy all of the above requirements shown in Figure 1.

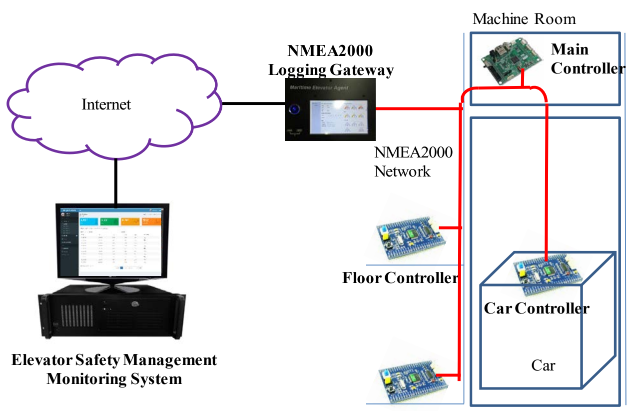

Figure 1. Overall System Configuration.

The monitoring system consists of a monitoring server, a logging gateway and controllers in the elevators which are connected with the NMEA 2000 logging gateway. The controllers consist of a main controller in machine room, a car controller in the cage and floor controllers in each floor. Server system software is designed using MEAN stack to easily implement and quickly deploy the system.

2.2 System Implementation

The NMEA 2000 logging gateway stores the sensor data locally, making safety status decisions by running the diagnosis prediction model trained in server. The gateway receives the broadcast messages through PGN, which contains control data of each controller and transforms them into the NMEA 0183-like messages. In-network processing module gathers the messages, pre-processes into events, and transmits them to the server and the diagnosis prediction model. They can be saved in the server to diagnose the events and send commands to controllers using PGN(NMEA 2000 messages). The engines of the diagnosis prediction model are algorithms coming from the server. The algorithms are trained model using big data collected from the elevator shown in Figure 2.

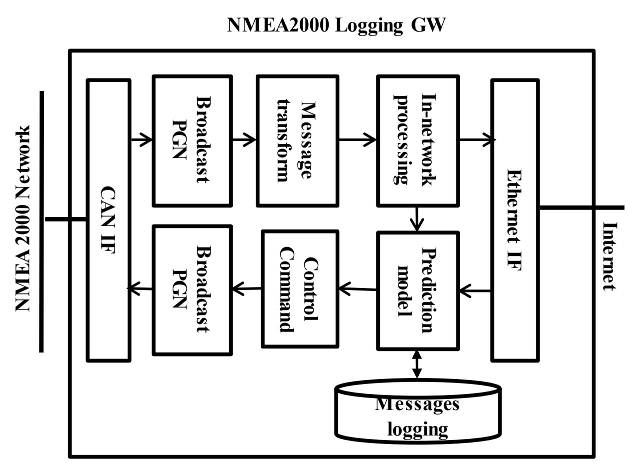

Figure 2. Logging Gateway Structure.

3. Prediction Model Performance

3.1 Test Environments

We generated labeled data using an elevator simulation program and made four diagnosis prediction models: loads, slopes with roll and pitch, slopes with platform tilt, and elevator car operation status as shown in Table 1[6].

Table 1. Features for Models

Models	Outputs	Features
Loads	• normal • biased load • overload	• total load • total four cells each • total time(sec)
Roll & Pitch Slopes	• normal • waiting stow • immediate stow	• total roll • total pitch • total time (sec)
Platform Slopes	• same as Roll & Pitch Slopes	• platform tilt • total time (sec)
Operation Status	• car arrived • not arrived	• floor level difference • running time (sec)

We labeled the roll and pitch slope data using the regulation in the DNV as shown in Table 2[7]. The platform slope data is labeled when in stowed condition, which is when slope is 11.17° or above for a duration of 8.5 seconds or when slope is 23.66° or above.

Table 2. Rules of Rolling and Pitching

Classification society		Rolling		Pitching	
		Operation condition	Stowed condition	Operation condition	Stowed condition
DNV	Angle	±10°	±22.5°	±5°	±7.5°
	Period	10 Second	-	7 Second	-

3.2 Test and Results

We simulated two test cases for each model. In the first test case, we used total load only and generated random car arrival time. In the second test case, we added total load feature of each load cells and total platform tilt feature to load model and roll and pitch slope model. Platform slope model was compared with and without roll and pitch slope. Operation status model used reasonable car arrival time to accept the normal within ±1 sec.

3.2.1 Load Prediction Model

We acquired the dataset with total load and each load of load cells. In the first two trials, we predicted the model using total load and sustained time, in the subsequent three trials, we use the previous trial features and each load cell's load features. The number of successes/failures and the ratio of accuracy and Kappa correlation are shown in Table 3.

3.2.2 Roll/Pitch Based Slope Prediction Model

We made the model using dataset with the sum of roll, the sum of pitch, and the time duration. The number of successes/failures and the ratio of accuracy and Kappa correlation are shown in Table 4.

Table 5, we predicted the model with results, which are from the subsequent three trials of roll & pitch feature and platform tilt feature.

3.2.3 Platform Based Slope Prediction Model

To get the labeled dataset of platform based slope

Table 3. Load Prediction Model Test Results

Trial	Dataset	Learning	Test	Fail	Success	Accuracy	š appa	cf
1	7,475	5,980	1,495	69	1,426	0.9538	0.9296	
2	5,585	4,468	1,117	54	1,063	0.9517	0.9260	
3	10,480	8,385	2,095	164	1,931	0.9217	0.8760	
	10,480	8,385	2,095	1	2,094	0.9995	0.9992	add local cells
4	13,472	10,778	2,694	188	2,506	0.9302	0.8900	
	13,472	10,778	2,694	0	2,694	1.0000	1.0000	add local cells
5	15,709	12,568	3,141	207	2,934	0.9341	0.8955	
	15,709	12,568	3,141	0	3,141	1.0000	1.0000	add local cells

Table 4. Roll/Pitch Based Slope Prediction Model Test Results

Trial	Dataset	Learning	Test	Fail	Success	Accuracy	š appa
1	3,370	2,696	674	5	669	0.9926	0.9886
2	2,560	2,048	512	3	509	0.9941	0.9910
3	4,745	3,796	949	1	948	0.9989	0.9984
4	6,186	4,950	1,236	11	1,225	0.9911	0.9864
5	7,129	5,704	1,425	7	1,418	0.9951	0.9925

Table 5. Roll/Pitch+Platform Based Slope Prediction Model Test Results

Trial	Dataset	Learning	Test	Fail	Success	Accuracy	š appa
3	4,745	3,796	949	0	949	1.0000	1.0000
4	6,186	4,950	1,236	0	1,236	1.0000	1.0000
5	7,129	5,704	1,425	1	1,424	0.9993	0.9989

prediction model, we set the simulated environment to the DNV guideline. We use the platform tilt feature which is obtained from Figure 3.

```
fpitch = pitch * 90.0 / 4096.0;
froll = roll * 180.0 / 4096.0;
platform_tilt = cos(fpitch * PI / 180.0) * cos (froll * PI / 180.0);
if (platform_tilt > 1.0) platform_tilt = 1.0;
if (platform_tilt < -1.0) platform_tilt = -1.0;
platform_tilt = acos(platform_tilt) * 180 / PI;
```

Figure 3. Platform Tilt Calculation Method.

Table 6 shows that in the first two trials, average roll and pitch values are used and in the following three trials, weighed roll and pitch values are used, which are 8.83° or above during 7 seconds and 23.66° and over.

Table 7, the test results are obtained from labeled data using platform tilt feature, summed roll feature, summed pitch feature, and sustained time feature in platform tilt event messages.

3.2.4 Car Operation Status Prediction Model

We assumed that motor speed is 60m/minute and height of one floor is 2m because the elevator inverter controls the motor speed. In the first two trials, we labeled data as a "success" when the car arrived in time and in the following three trials we labeled data as a "success" when car arrival time is in ±1 second margin as shown Table 8.

3.3 Analysis of the Results

The analysis results were recorded using 80% random sampling of labeled event message data sets for machine learning[8-10], which were generated in cars and collected automatically in the server, and the remaining 20% from the input of the learned prediction model. Evaluation method was decided out of accuracy and the Kappa correlation coefficient. After the analysis, we determined that additional features enhanced accuracies in every model. In the operation status model case, the accuracy is enhanced, but the Kappa correlation coefficients are dropped[11].

3.3.1 Load Prediction Model

Figure 4 using total load features and total holding time features, accuracy to determine whether event messages are normal, overload and biased load is between 0.92 and

Table 6. Platform Based Slope Prediction Model Test Results

Trial	Dataset	Learning	Test	Fail	Success	Accuracy	š appa
1	10,500	8,400	2,100	164	1,905	0.9071	0.8571
2	8,330	6,664	1,666	188	1,523	0.9142	0.8677
3	30,261	24,209	6,052	133	5,919	0.9780	0.9659
4	39,248	31,399	7,849	183	7,666	0.9767	0.9640
5	45,607	36,486	9,121	179	8,942	0.9804	0.9697

Table 7. Roll/Pitch Prediction Model using Platform Tilt Feature Event Test Results

Trial	Dataset	Learning	Test	Fail	Success	Accuracy	š appa
3	4,745	3,796	949	60	889	0.9368	0.9036
4	6,186	4,950	1,236	73	1,163	0.9409	0.9102
5	7,129	5,704	1,425	104	1,321	0.9270	0.8885

Table 8. Car Operation Status Prediction Model Test Results

Trial	Dataset	Learning	Test	Fail	Success	Accuracy	š appa
1	5,080	4,064	1,016	30	986	0.9705	0.9302
2	3,815	3,052	763	39	724	0.9489	0.8803
3	7,530	6,024	1,506	60	1,446	0.9602	0.7966
4	9,726	7,781	1,945	81	1,864	0.9584	0.7587
5	11,372	9,098	2,274	59	2,215	0.9741	0.8556

0.95, Kappa correlation coefficient is considerably high between 0.88 and 0.92.

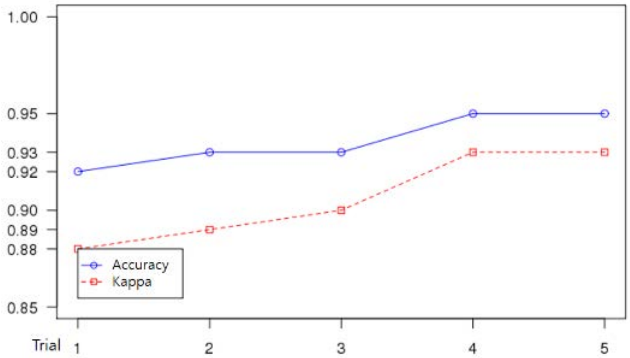

Figure 4. Accuracy and Kappa of Load Prediction Model.

As shown in Figure 5, we test with above features, by adding total loads feature for 4 load cells, resulting in accuracy and Kappa correlation coefficient of close to 1.00.

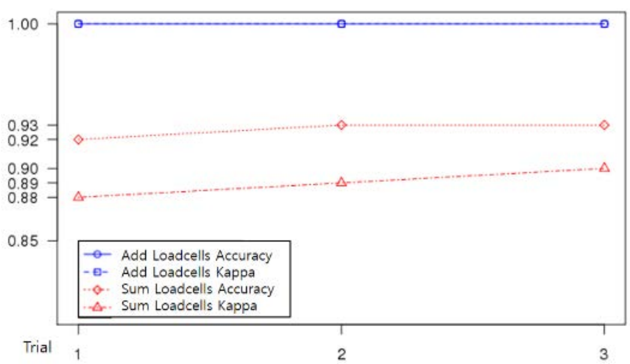

Figure 5. Accuracy and Kappa of Load Prediction Model with load cell features.

3.3.2 Roll/Pitch Based Slope Prediction Model

The prediction model which has 99% or above of accuracy and Kappa correlation coefficient, can predict the status of cars, whether it is normal, immediate stow or waiting stow, using total roll values, total pitch value and status holding time features as shown in Figure 6.

Adding total platform weight features to total roll values, total pitch value and status holding time features, the prediction model's accuracy and Kappa correlation coefficient were close to 1.00. Therefore, in the case of roll & pitch slopes and platform slopes, it could have 0.99 or above of accuracy, without adding platform slope related features as shown in Figure 7.

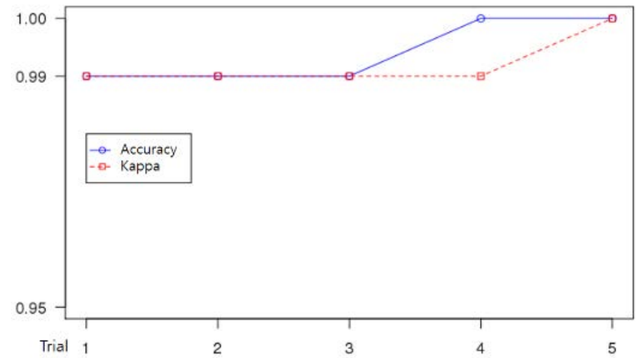

Figure 6. Accuracy and Kappa of Roll/Pitch based slope prediction model.

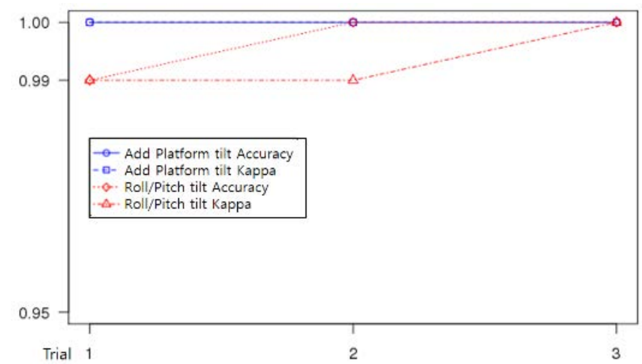

Figure 7. Accuracy and Kappa of Roll/Pitch Based Slope Prediction Model with Platform Tilt Features.

3.3.3 Platform Based Slope Prediction Model

Using platform slopes which is unified roll and pitch features, it shows the accuracy of 0.98 in the case of platform slopes by weighted slope and time, while the accuracy is 0.91 in the case of platform slopes by average slope and time.

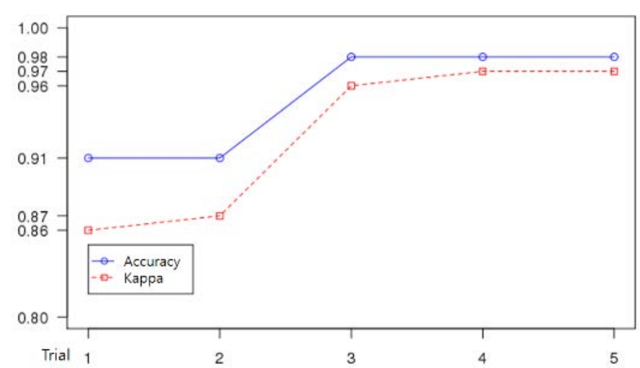

Figure 8. Accuracy and Kappa of Platform Based Slope Prediction Model.

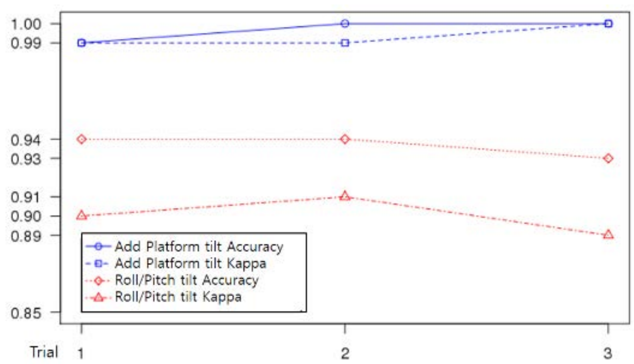

Figure 9. Comparison of Accuracy and Kappa of Roll/pitch Based Slope Prediction Model with/without Platform Tilt Features.

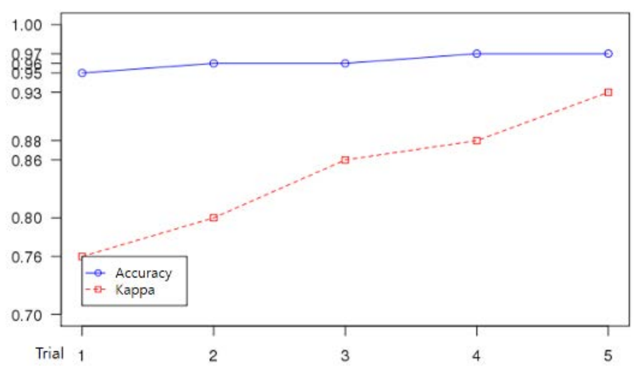

Figure 10. Accuracy and Kappa of Car Operation Status Prediction Model.

Figure 8 shows the determination of results for event messages independently, Figure 9 shown in the case that used platform features and compared the results with roll & pitch slopes, which measured below 0.04 of accuracy. Therefore, we can handle slope diversity by using roll & pitch slopes without calculating platform slopes separately.

3.3.4 Car Operation Status Prediction Model

Car operation status prediction model measures whether car operation is normal or not, with floor movement pitch and arrival time pitch. In the case of calculating accurately without tolerance for arrival time pitch, it shows accuracy of 0.95 ~ 0.96. On the other hand, Kappa correlation coefficient is only 0.81 for decision.

However, deciding the results with tolerance of ± 1 second, it shows accuracy of 0.97 and almost completes consistency with the Kappa correlation coefficient of 0.86 or above.

4. Conclusion

We designed and implemented a safety elevator monitoring system based on the NMEA 2000 network. The logging gateway provides diagnosis prediction model trained by big data on the server for the marine elevator maintenance.

With analyzing the results of the above 7 tests, we can conclude the followings:

- Among the elevator car operation status models, Kappa correlation coefficient is 0.81 or above for overall prediction models except for the case of accurate arrival time as evaluation criteria, which is considered completely consistent.
- Loads model should include total weight feature for 4 load cells to decide accurately.
- Role & Pitch Slopes model and Platform Slopes model can secure accuracy 0.99 over above, without using a separate single platform slope.

Therefore, we conclude that it is possible to generate the prediction model with satisfactory accuracy without using complex deep learning algorithms, such as RNN (Recurrent Neural Network) etc., in order to sample features.

5. References

1. Jayavel K, Nagarajan V. Survey of Migration, Integration and Interconnection Techniques of Data Centric Networks to Internet- Towards Internet of Things (IoT), Indian Journal of Science and Technology. 2016 February; 9(8):1–7.
2. Nick Heath. Keeping the world's elevators running smoothly with machine learning and IoT. Posted in March 2, 2015: Available from: http://www.zdnet.com/article.
3. NMEA, NMEA 2000 - Appendices A & B - Parameter Groups (PGNs) NMEA Network Messages, VERSION 2.000, January 2013.
4. Aggarwal, Charu C. (Ed.), Managing and Mining Sensor Data, Springer 2016.
5. Roman Kern. Feature Engineering. http://kti.tugraz.at/staff/denis/- courses/kddm1/featureengineering.pdf. Date accessed: 29/10/2015.
6. Maheshwari V, Prasanna M. Generation of Test Case using Automation in Software Systems – A Review, Indian Journal of Science and Technology. 2015 Dec; 8(35):1–8.
7. DNV(1987), Rules for Certification of Lifts in Ships, Mobile Offshore Units and Offshore Installations, 1987.
8. DMLC(Distributed Machine Learning Community) XGBoost Parameters. 2016. https://github.com/dmlc/xgboost/blob/master/doc/parameter.md.

9. Cynthia Deb, M. Ramesh Nachiappan, M. Elangovan, V. Sugumaran. Fault Diagnosis of a Single Point Cutting Tool using Statistical Features by Random Forest Classifier. Indian Journal of Science and Technology. 2016; 9(33):1–8.
10. Preeti Aggarwal and Deepak Dahiya. Contribution of Four Class Labeled Attributes of Kdd Dataset on Detection and False Alarm Rate for Intrusion Detection System. Indian Journal of Science and Technology. 2016; 9(5):1–8.
11. Wikipedia, Cohen's kappa. 2016a. https://en.wikipedia.org/wiki/Cohen%27s_kappa.