CLASSIFICATION OF INDUSTRIAL CONVEYOR LOAD STATUS USING RUBBER BELT TENSION AND DEEP LEARNING MODELS

T. Žvirblis[1], L. Petkevičius[2], D. Bzinkowski[3], M. Rucki[3], A. Kilikevičius[1]

1 Institute of Mechanical Science, Vilnius Gediminas Technical University, LT-03224 Vilnius, Lithuania
2 Institute of Computer Science Vilnius University Vilnius, Lithuania
3 Kazimierz Pulaski University of Technology and Humanities in Radom, Poland

BACKGROUND

Industrial conveyors are used in production process to ensure its efficiency in terms of timely transportation of loose materials and assembled units [1]. In industrial applications, new conveyor belt solutions may substantially reduce overall production costs [2]. The investigated object was the model of belt conveyor (CB) with strain gauges placed on the roller to measure belt strain in real-time work conditions [3].

OBJECTIVES

1. to develop ML models for classification loaded and unloaded conditions of CB;
2. to identify optimal signal length of tensile pressure which enables achieving the best classification accuracy;
3. to evaluate the robustness of the best model for distinguishing CB conditions when CB and measurement system are not calibrated.

METHODS

Test campaign included measuring static tension under 2 kg load in different points of the CB and measurements in dynamic conditions. The experiment design was created based on the time stamps as follows: for the first 5 s there was no load, then for 15 s – load of 2 kg and for the last 5 s – no load (Fig. 1). There were developed CORBEL dataset and 5 ML models (LR, SVM, RF, LSTM, and Transformer) for distinguishing loaded and unloaded conditions of CB.

RESULTS

Shallow machine learning models:

- Sixteen time domain parameters were estimated instead of raw signals in order to reduce the dimension of classification model input for LR, SVM, and RF models.
- Thus, all signals of 0.2 s (80 points), 0.4 s (160 points), 0.8 s (320 points), 1.6 s (640 points), 3.2 s (1280 points) and 5.0 s (2000 points) length were transformed to estimates of 16 parameters.
- In LR, SVM, and RF models the accuracy of the model increased by 4% on the average each time when the signal length was doubled.
- RF was the most accurate among the three models and was able to classify 3.2 s and 5.0 s-length signals with an accuracy of 79% and 78%, which was by 3% higher than that of LR or SVM. (Table 1).

Deep learning models:

- LSTM and Transformer models were developed to classify raw CB signals. Each model was trained with signals of different lengths (0.2 s, 0.4 s, 0.8 s, 1.6 s, 3.2 s, and 5.0 s) by repeating the training for 20 epochs.
- The accuracy of LSTM and Transformer models increased very rapidly with increasing signal length and an accuracy of 100% was achieved when using both models with the longest signals (Table 1).
- The accuracy of Transformer increased on average by 8% when doubling the signal length and after training with the longest signal of 5.0 s, its accuracy reached 100% (Table 1).
- The accuracy of LSTM model grew even faster and after training with the 1.6 s signal, the accuracy reached 100% (Table 1).

Model robustness:

- Random noise had almost no effect on the accuracy of the model until the noise reached 20-times lower value of the standard deviation (Fig. 3).
- Drifted noise had greater effect on the accuracy of the model, although under relatively large standard deviation the model was able to classify with the accuracy of >90% (Fig. 3).

Table 1. Classification accuracy for all models.

Model	Signal length, s					
	0.2	0.4	0.8	1.6	3.2	5.0
Accuracy, %						
LR	57	61	65	69	72	**76**
SVM	58	62	66	71	74	**76**
RF	60	62	67	74	**79**	78
Transformer	60	63	69	81	92	**100**
LSTM	72	77	98	**100**	**100**	**100**

Fig. 1. Conveyor belt tension signals of both strain gauges.

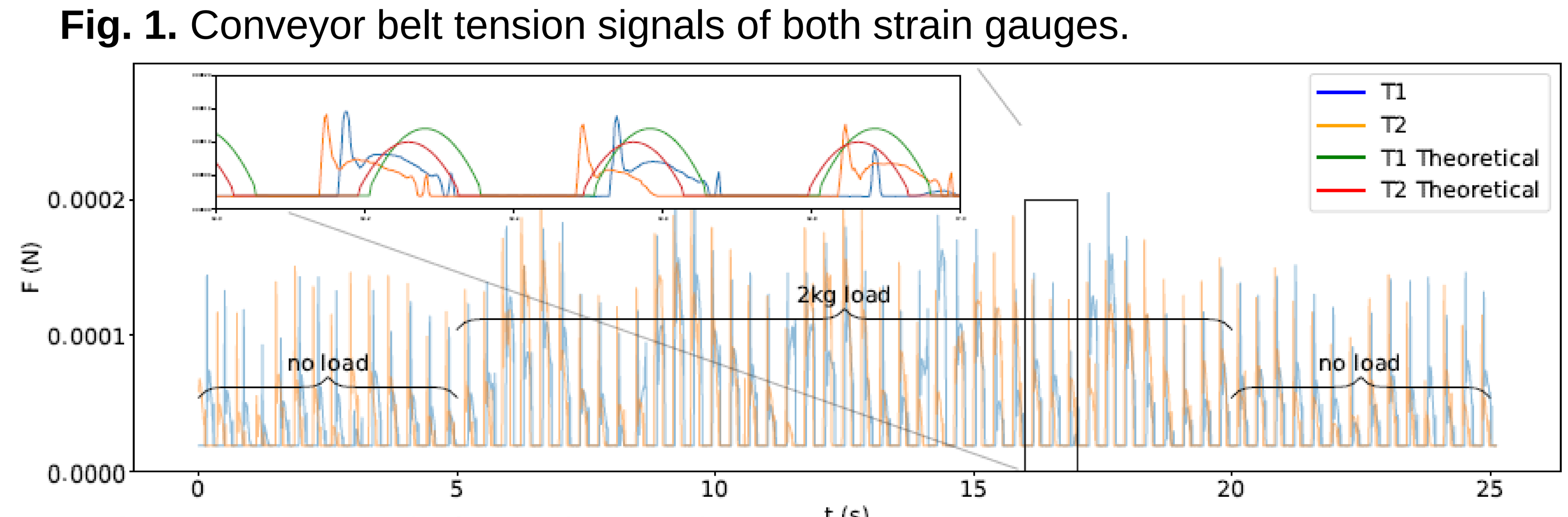


Fig. 2. Conveyor belt tension peak.

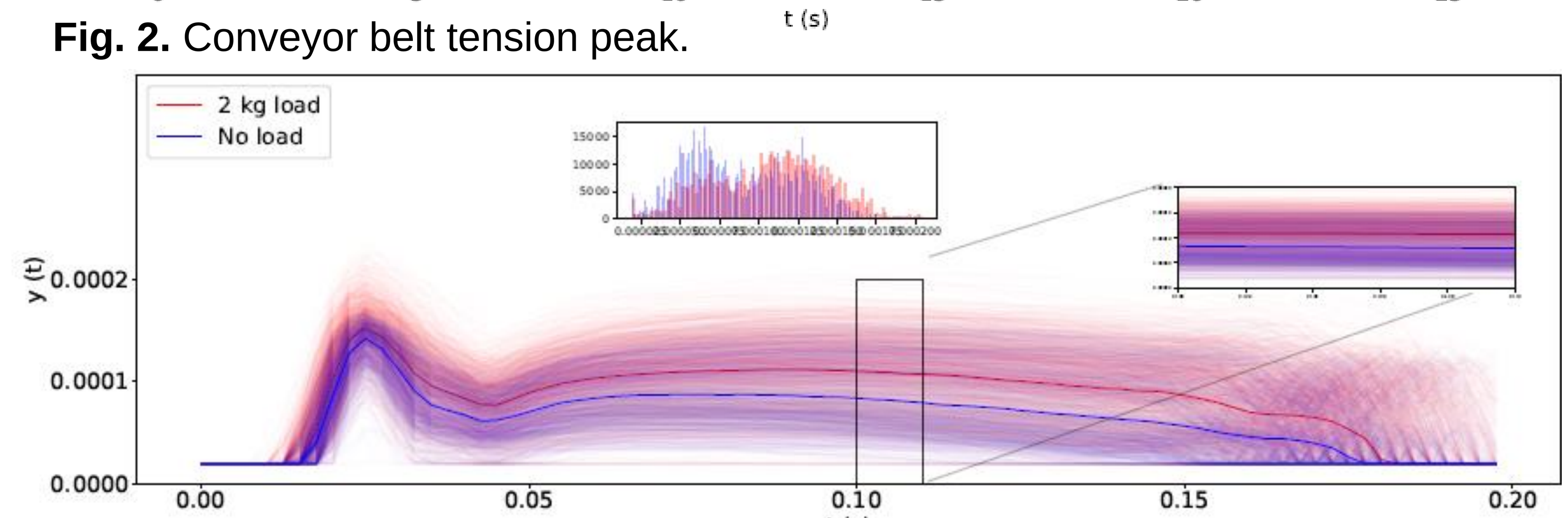
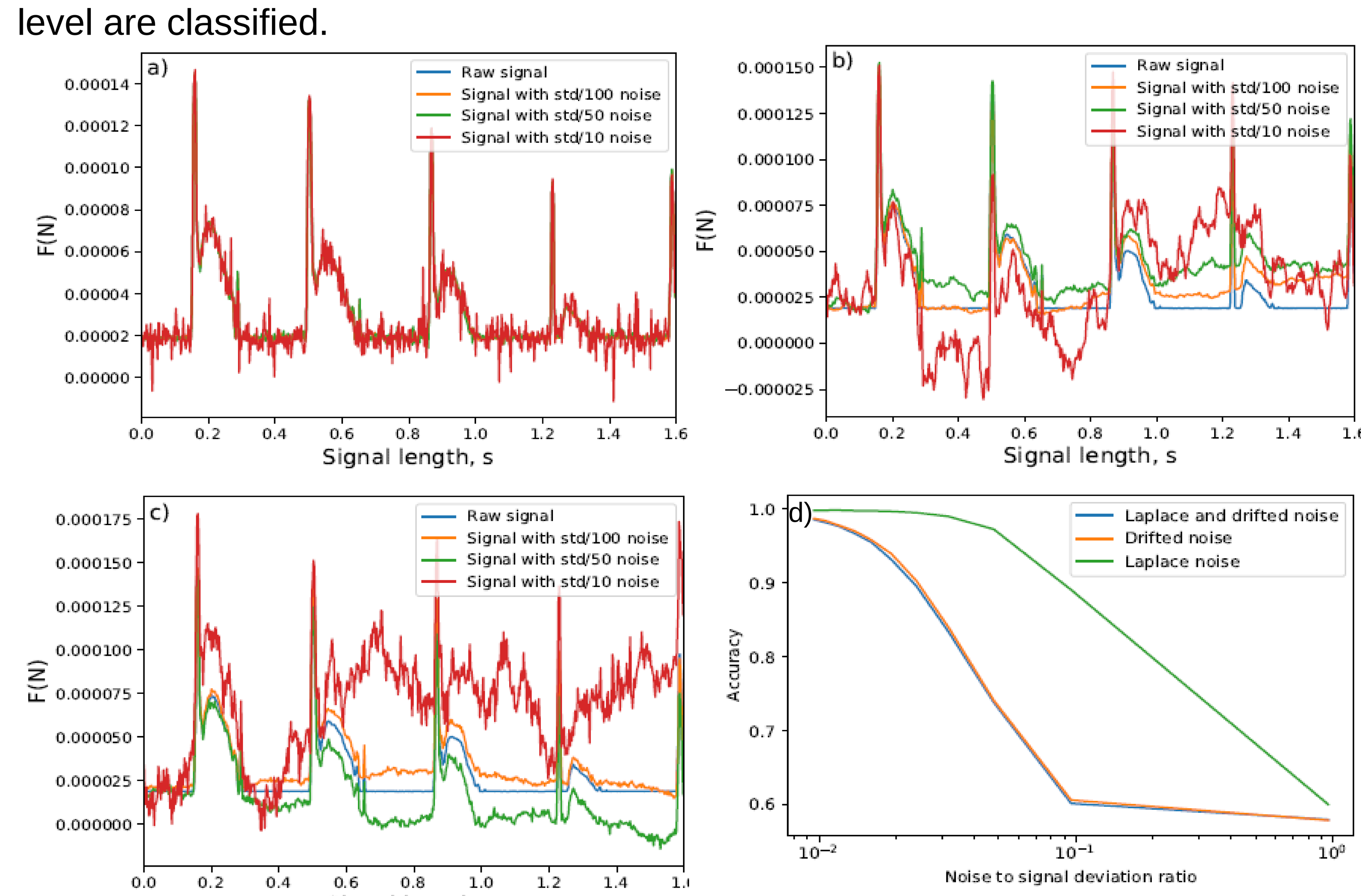


Fig. 3. LSTM robustness: a) random Laplace noise; b) drifted noise; c) random + drifted noise; d) classification accuracy when the signals of different noise type and level are classified.



CONCLUSIONS

The proposed LSTM and Transformer models were able to classify signals precisely with accuracy, precision, recall and F1-score of 100%. Shallow models such as LR, SVM, and RF performed considerably worse in classification of different CB conditions.

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