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MACHINE LEARNING BASED APPROACH TO A CRANE LOAD ESTIMATION

Zastosowanie uczenia maszynowego w estymacji obciążenia suwnicy pomostowej

Abstract: *In the presence of increasing demands for safety and efficiency of material handling systems, the development of advanced supervisory control, monitoring, data acquisition and diagnostic systems is involved, especially for large industrial cranes. The important part of such systems is the continuous monitoring of a crane load. The crane load monitoring system proposed in the paper is based on a fuzzy model that estimates a payload mass transferred by a crane based on measuring the crane girder deflection and trolley position. The model was identified using the fuzzy subtractive clustering and least mean square with the data collected during experiments carried out on the laboratory scaled overhead crane.*

Keywords: crane load monitoring, fuzzy model, machine learning

Streszczenie: *Coraz większe wymagania odnośnie bezpieczeństwa i wydajności procesu transportu technologicznego kierują uwagę na rozwój coraz bardziej zaawansowanych systemów nadrzędnego sterowania, monitorowania, akwizycji danych i diagnostyki dźwignic. Ważnym elementem takiego systemu jest pomiar i monitorowanie obciążenia dźwignicy. Zaproponowany w pracy system monitorowania obciążenia suwnicy pomostowej został oparty na rozmytym modelu estymującym masę ładunku transportowanego przez suwnicę na podstawie odkształcenia dźwigara mostu suwnicy oraz pozycji wciągarki. Przedstawiono dwustopniową procedurę identyfikacji modelu z zastosowaniem metod grupowania rozmytego oraz najmniejszych kwadratów, którą przeprowadzono dla danych uzyskanych z eksperymentów wykonanych na stanowisku laboratoryjnym.*

Słowa kluczowe: monitorowanie obciążenia suwnicy, model rozmyty, uczenie maszynowe

1. Introduction

Cranes are widely used in many industries for transporting heavy and high-volume loads. The different types of cranes, such as overhead, gantry, tower and boom cranes are extensively used in factories, shipyards, warehouses, and construction. The large industrial cranes carry out transportation operations in the presence of a large impact load and mechanical stresses acting on the crane's structure and equipment. The increasing demands for safety and efficiency of crane operations require the development and implementation of advanced supervisory control, monitoring and diagnostic systems for supporting maintenance and decision-making processes to reduce downtimes, operations, and maintenance costs [3, 4, 7, 8]. The important part of such system is the continuous monitoring of a crane load. The crane load monitoring system can be developed using crane scales widely offered by crane companies or multi sensors applications created for specific requirements [1, 6].

Crane scales are commonly used in material handling systems for weighting a hanging load. There are variety of crane scale models, with different range, weighting capacity and accuracy that can be adapted for a given application and specific requirements. For load monitoring applications there are offered different sophisticated solutions, resistant to extreme conditions, temperature, dust, and vibrations, also with wireless data transmission possibility when the load cell cable cannot be provided due to the large distance or risk of cable damage. However, in industrial practice, there are still many problems that can occur and accumulate affecting reliability of load monitoring systems, requiring specific and expensive solutions, and making crane scale based systems difficult to apply, e.g. lack of headroom for installation of a crane scale, a nonstandard oversized load, disturbances on wireless communication with the simultaneous problem of wire power and data transmission.

The paper presents the machine-learning approach for estimation a payload mass lifted by an overhead travelling crane. A fuzzy model is used to estimate a payload weight based on the crane girder deflection and taking into account location of a trolley on the crane's bridge. The experiments on the laboratory scaled overhead traveling crane were carried out to collect the learning data used for identification of a fuzzy model. The identification procedure was based on the fuzzy subtractive clustering and least mean square (LMS).

The rest of the paper is organized as follows. Section two presents the experimental setup built on the laboratory stand for crane load monitoring. Section three describes the identification process, while section four presents the results. Section five delivers conclusions.

2. Experimental setup for crane load monitoring

The load monitoring system has been prototyped on the laboratory stand (fig. 1), the double-girder overhead travelling crane with hoisting capacity 150 kg, span of the girders

$L = 2.4$ m, trolley wheelbase $a = 0.3$ m and the trolley travelling range 1.8 m. The crane's bridge, trolley and hoisting are driven by worm gear three-phase motors supplied from single-phase frequency inverters. The schematic view of the measurement system used for estimation of payload mass m transferred by a trolley along the crane's girder is shown in fig. 2. The trolley position x on the girder is measured using the incremental encoder with resolutions 200 ppr attached to the trolley wheel, while the strain gauge supplied by the ADAM 3016 input module is applied to measure the strain in the middle point of the girder. The data acquisition is performed using the PC equipped with PCI 1710 measurement card and Matlab software.

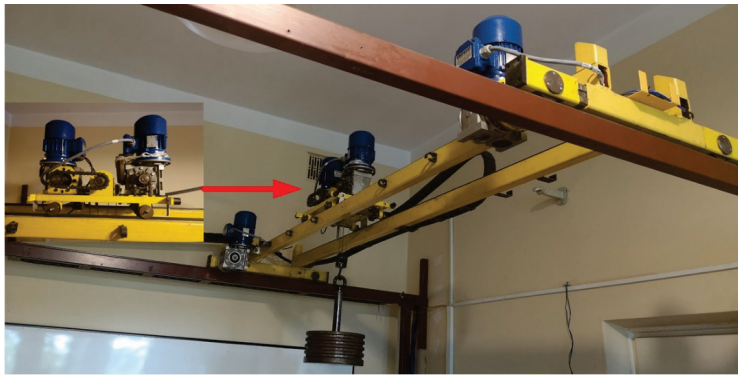


Fig. 1. Laboratory scaled overhead travelling crane

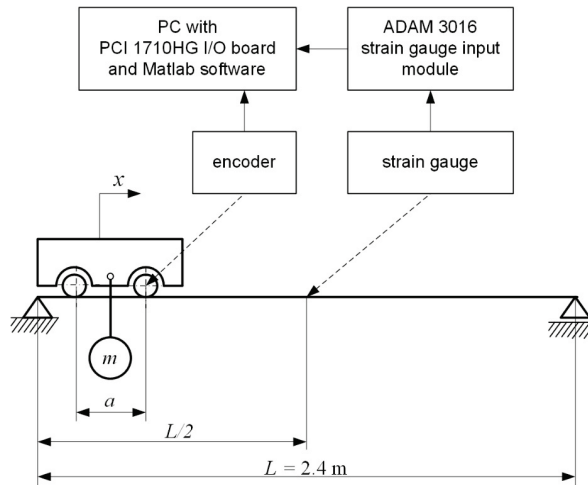


Fig. 2. Schematic view of the measurement system

The mass of a payload m is estimated by a Takagi-Sugeno-Kang (TSK) fuzzy model [9, 10] (fig. 3) based on the two input variables, trolley position x and strain of a girder ε .

The relation between input and output of the TSK fuzzy model is represented by a set of fuzzy rules

$$R_k: \text{IF } x \text{ is } A_k \text{ and } e \text{ is } B_k \text{ THEN } \hat{m} = p_{k1}x + p_{k2}\varepsilon + p_{k3} \quad (1)$$

where $k = 1, 2, \dots, N$, A and B are fuzzy sets defined in x and ε input space, p_{k1} , p_{k2} and p_{k3} are the parameters of the linear function defined in the consequent part of fuzzy relation R_k .

The fuzzy sets A and B are defined as

$$\begin{aligned} A &= \{x, \mu_A(x); x \in X\} \\ B &= \{\varepsilon, \mu_B(\varepsilon); \varepsilon \in E\} \end{aligned} \quad (2)$$

where $\mu(x)$ and $\mu(\varepsilon)$ are assumed to be Gaussian membership functions

$$\begin{aligned} \mu_A(x) &= \exp\left(-\frac{(x - a_A)^2}{2\sigma_A^2}\right) \\ \mu_B(\varepsilon) &= \exp\left(-\frac{(\varepsilon - a_B)^2}{2\sigma_B^2}\right) \end{aligned} \quad (3)$$

a_A , a_B are expected values, and σ_A and σ_B are standard deviations.

The model output is calculated as the weighted average of all rules outputs

$$\hat{m} = \frac{\sum_{k=1}^N w_k \hat{m}_k}{\sum_{k=1}^N w_k} \quad (4)$$

where weight of a rule is determined as follows

$$w_k = \mu_A(x)\mu_B(\varepsilon) \quad (5)$$

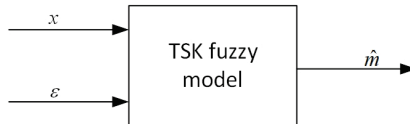


Fig. 3. TSK fuzzy model for estimation of payload mass

The TSK fuzzy model is usually designed in two steps. In the first step, the fuzzy sets (membership functions) in the rule antecedents are determined. This can be done using heuristic knowledge of the process, or by data-driven techniques. In the second step, the parameters of the consequent functions are estimated. In this paper, the fuzzy subtractive clustering is applied in the first step to partition the input space into clusters corresponding to the rules antecedents. Thus, the first step leads to determine fuzzy rules and membership functions parameters. In the next step, the least square method is employed to estimate the parameters of rule consequents.

3. Fuzzy model identification

The training data for identification process was collected in the Matlab by carrying out five experiments on the laboratory stand with payload masses 20, 40, 60, 80 and 100 kg transferred by the trolley along the girders and measuring the trolley position and relative strain of the girder with sample time 0.1 s. In each experiments trolley started moving from initial position $x = 0$ (left-hand side position of the trolley as it is depicted in fig. 2) to final position $x = 1.8$ m. It was assumed that payload mass estimation is performed within the trolley position range $x = [0.4, 1.4]$, thus, the 754 data points (fig. 3) were taken from this measurement range as the learning and validation data with proportion 70/30.

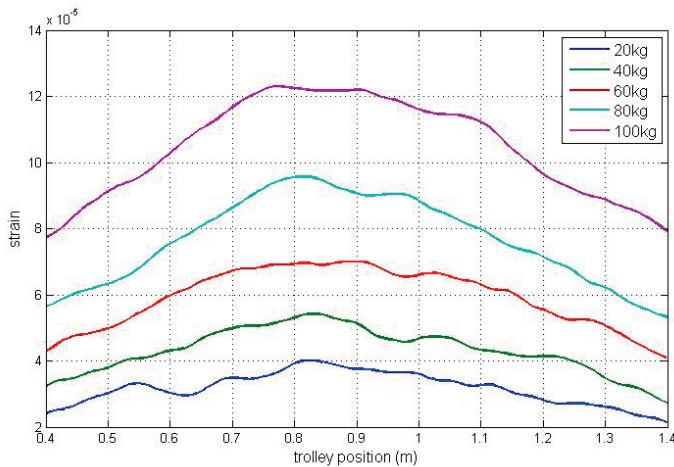


Fig. 4. Relative strain versus position of the trolley

The two step identification process is employed to determine the fuzzy relations and parameters of a fuzzy estimator of payload mass. In the first step, the subtractive clustering algorithm [2] is applied to find the fuzzy rules and determine the membership functions parameters by partitioning the input space samples into clusters and determining its centers

by choosing the data points with the highest potential. The iterative procedure starts to calculate a potential $P(d_i)$ of each i -th data point to be a cluster center based on a function of its distance to all other data points:

$$P(d_i) = \sum_{j=1}^n \exp \left(- \frac{\|d_i - d_j\|^2}{\left(\frac{r_a}{2}\right)^2} \right) \quad (6)$$

where r_a is a positive constant called cluster radius, n is the number of samples.

The data point with the highest potential is chosen as the first cluster center. In each next k -th step, the potential of all remaining data points are reduced according to their distance to the cluster center c_{k-1} selected in the previous $k-1$ step:

$$P(d_i) = P(d_i) - P(c_{k-1}) \cdot \exp \left(- \frac{\|d_j - c_{k-1}\|^2}{\left(\frac{r_b}{2}\right)^2} \right), \quad r_b = b \cdot r_a \quad (7)$$

where b is positive parameter called squash factor.

A termination of the algorithm is implemented by defining the upper and lower thresholds, as recommended in [2]. If the highest potential in the k -th step P_k is above the upper threshold (8), the data point d_k is accepted as the new cluster center, while if the condition (9) is satisfied the data point d_k is rejected and algorithm is terminated.

$$P_k > \varepsilon_1 P_1 \quad (8)$$

$$P_k < \varepsilon_2 P_1 \quad (9)$$

where P_1 is the potential of the data point chosen as the first cluster center, ε_1 and ε_2 are positive parameters called accept and reject ratios, respectively.

If conditions (8) and (9) are both violated, the shortest distance d_{min} between d_k and all previously found cluster centers is chosen to check condition (10). The data point is accepted as the cluster center if condition (10) is satisfied, otherwise the data point with the next highest potential are tested using (10).

$$\frac{d_{min}}{r_a} + \frac{P_k}{P_1} \geq 1 \quad (10)$$

After all antecedents of rule based fuzzy system are determined using the fuzzy clustering method, the LMS is applied to estimate the consequent parameters of fuzzy rule (1). The vector of the consequent parameters of the k -th rule is estimated as follows

$$\hat{\theta}_k = (X_k^T X_k)^{-1} X_k^T m_k \quad (11)$$

where $\hat{\theta}_k = [\hat{p}_{k1}, \hat{p}_{k2}, \hat{p}_{k2}]^T$, m_k is the output pattern vector, and X_k is the weighted design matrix created based on the n input data points with their corresponding normalized rule weights:

$$X_k = \begin{bmatrix} \bar{w}_k^{(1)} x^{(1)} & \bar{w}_k^{(1)} \mathcal{E}^{(1)} & \bar{w}_k^{(1)} \\ \bar{w}_k^{(2)} x^{(2)} & \bar{w}_k^{(2)} \mathcal{E}^{(2)} & \bar{w}_k^{(2)} \\ \vdots & \vdots & \vdots \\ \bar{w}_k^{(n)} x^{(n)} & \bar{w}_k^{(n)} \mathcal{E}^{(n)} & \bar{w}_k^{(n)} \end{bmatrix},$$

$$\bar{w}_k = \frac{w_k}{N}, \text{ where } N \text{ is the number of if-then rules.}$$

$$\sum_{i=1} w_i$$

4. Results

The fuzzy model identification was performed assuming in the clustering method that the accept and reject ratios as $\varepsilon_1 = 0.5$ and $\varepsilon_2 = 0.15$, $r_a = 0.5$, and changing the squash factor value from 1.2 to 0.8 and 0.5 due to its influence on the number of if-then rules. It resulted in the three TSK fuzzy models with 9, 15 and 22 fuzzy rules obtained for 1.2, 0.8 and 0.5 values of the squash factor, respectively. The relative estimation error versus trolley position for TSK fuzzy models are presented in figures 4, 5 and 6. Table 1 presents the maximum and mean values of estimation errors.

The model accuracy increases with increasing the model complexity. The root mean square error (RMSE) is 0.0224, 0.0149 and 0.0072 for the models with 9, 15 and 22 rules, respectively. Obviously, the estimation accuracy rises with the increase of the payload mass. In case of the fuzzy model with 9 rules and for the 20 kg payload mass, the maximum of the relative error is 0.1079, while for the 100 kg the estimation error does not exceeds 0.0127 (Tab. 1). Similarly, the model with 22 rules estimates 20 kg and 100 kg payload mass with the maximum value of the relative error 0.0481 and 0.006, respectively. The further improvement in estimation and extension of the measurement range can be obtained by measuring the girder strain at multiple points.

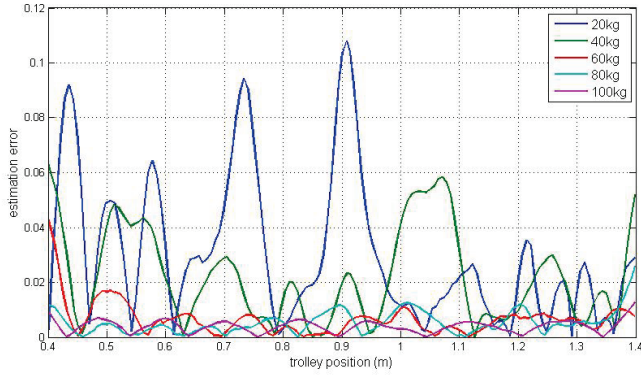


Fig. 5. Relative estimation error for the TSK fuzzy model with 9 if-then rules

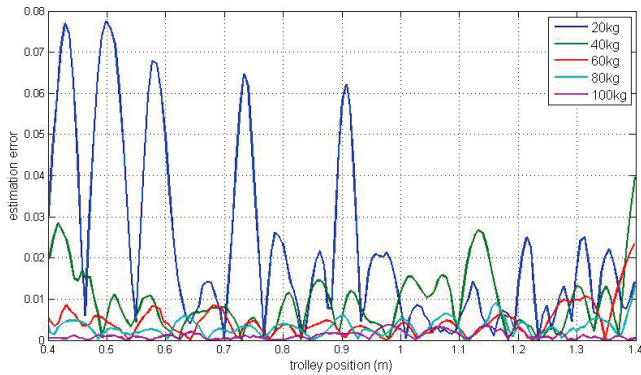


Fig. 6. Relative estimation error for the TSK fuzzy model with 15 if-then rules

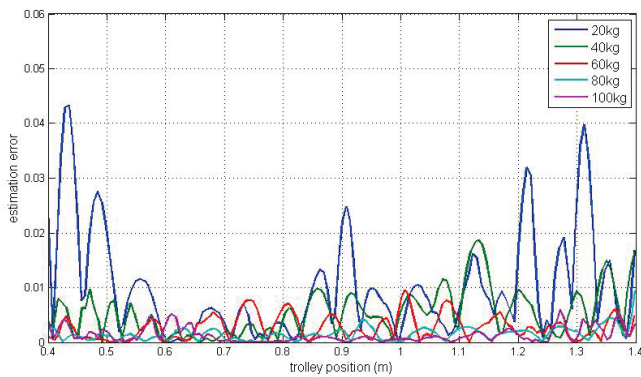


Fig. 7. Relative estimation error for the TSK fuzzy model with 22 if-then rules

Table 1

Maximum and mean values of the relative estimation error

		Number of if-then rules in TSK fuzzy model				
		9	15		22	
		relative error				
estimated mass (kg)	maximum	mean	maximum	mean	maximum	mean
20	0.1079	0.0303	0.0775	0.0223	0.0481	0.0102
40	0.0694	0.0222	0.0395	0.0093	0.0187	0.0053
60	0.0455	0.0066	0.0234	0.0044	0.0095	0.0028
80	0.0261	0.0054	0.0134	0.0031	0.0094	0.0015
100	0.0127	0.0039	0.0037	0.0012	0.0060	0.0013

5. Conclusions

The paper presents the data-driven approach for designing a fuzzy model to estimate a payload mass lifted by an overhead travelling crane system based on the crane girder deflection. The model identification procedure was based on the fuzzy subtractive clustering and LMS algorithm, and tested for the learning data collected during experiments carried out on the laboratory stand. The satisfactory results proved that the proposed approach can be implemented in a crane load monitoring system and can be used redundantly with other measurement equipment (e.g. crane scales) to enhance the reliability of monitoring or diagnostic system.

Acknowledgement

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6. References

1. Balkan T.: A load control system for mobile crane, Mechanics Research Communications, Vol. 23, No. 4, 1996.
2. Chiu S. L.: Fuzzy model identification based in cluster estimation, Journal of Intelligent and Fuzzy Systems 2, 1994.

3. Gąska D., Margielewicz J., Haniszewski T., Matyja T., Konieczny Ł., Chróst P.: Numerical identification of the overhead traveling crane's dynamic factor caused by lifting the load off the ground, *Journal of Measurements in Engineering* 3 (1), 2015.
4. Haniszewski, T.: Modeling the dynamics of cargo lifting process by overhead crane for dynamic overload factor estimation, *Journal of Vibroengineering*, 19 (1), 2017.
5. Jang J.-S. R., Sun C.-T., Mizutani E.: *Neuro-Fuzzy and soft computing, a computational approach to learning and machine intelligence*, Prentice Hall, NJ, 1997.
6. Kalairassan G., Boopathi M., Mohan R.M.: Analysis of load monitoring system in hydraulic mobile cranes, *IOP Conf. Series: Material Science and Engineering* 263 (2017) 062045.
7. Ramli L., Mohamed Z., Abdullahi A.M., Jaafar H.I., Lazim, I.M.: Control strategies for crane systems: A comprehensive review, *Mechanical Systems and Signal Processing* 95, 2017.
8. Smoczek J., Szytko J.: Evolutionary algorithm-based design of a fuzzy TBF predictive model and TSK fuzzy anti-sway crane control system, *Engineering Applications of Artificial Intelligence* 28, 2014.
9. Sugeno M., Kang T.: Structure identification of fuzzy model. *Fuzzy Sets and Systems* 28, 1988.
10. Takagi T., Sugeno M.: Fuzzy identification of systems and its application to modeling and control. *IEEE Trans. Systems, Man and Cybernetics* 15 (1), 1985.