

Interval Analysis Approach to Prototype the Robust Control of the Laboratory Overhead Crane

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Abstract. The paper describes the software-hardware equipment and control-measurement solutions elaborated to prototype the laboratory scaled overhead crane control system. The novelty approach to crane dynamic system modelling and fuzzy robust control scheme design is presented. The iterative procedure for designing a fuzzy scheduling control scheme is developed based on the interval analysis of discrete-time closed-loop system characteristic polynomial coefficients in the presence of rope length and mass of a payload variation to select the minimum set of operating points corresponding to the midpoints of membership functions at which the linear controllers are determined through desired poles assignment. The experimental results obtained on the laboratory stand are presented.

Keywords: overhead crane, control system prototyping, fuzzy scheduling, interval arithmetic

1. Introduction

The automation of cranes operations is very important owing to necessity of ensuring the safety and efficiency of the transportation process, that is involved by requirements of enhancing the productivity of manufacturing processes. Those requirements motivate scientists and engineers to develop and implement solutions for crane control system which face up to the following problem: transfer a payload as fast as possible from point to point with avoidance of collision with obstacles, and precise positioning at a final point with reduction of sway of a payload suspended at the end of a rope. The different control schemes, developed for example based on input and command shaping [1], optimal control theory [2, 3], sliding mode control [4], and robust feedback controllers [5] have been addressed to the crane control problem for decades. However both, open- and closed-loop methods cause some well known problems in implementation. The open loop anti-sway crane control are sensitive to disturbances owing to lack of sway angle of a payload feedback. There is not always the possibility to build a reliable sway angle measurement system using encoders, thus, some works report the Hall-effect magnetic sensors [6-7], machine visions [8-10] and stereovision-based systems [11].

Furthermore, the soft computing techniques are widely employed to the considered problem. The fuzzy logic is used to create linguistic-rule-based fuzzy controllers [12], PID gains tuning [13-14] and



sliding mode control [13]. Membership functions tuning techniques have been developed based on an inverse dynamic [15], gradient algorithm [16], genetic algorithm [17], fuzzy clustering methods [18], and through applying artificial neural network [19].

The proposed in the literature methods are mostly applied for only membership functions tuning for a fixed number of fuzzy rules, and the robustness to mass of a payload is frequently neglected. Thus, the paper presents the novelty approach to crane dynamic system modelling and prototyping the robust control scheme with fuzzy interpolation of linear controller parameters in the presence of varying rope length and mass of a payload. The control system design is based on the a discrete-time crane dynamic model and interval analysis of closed-loop system characteristic polynomial coefficients. The iterative procedure for membership functions tuning, and creating the complete and coherent rule base is described. The presented method was used to prototype the control system for the laboratory scaled overhead crane. The fuzzy control scheme was implemented using structured text on the PAC system with RX3i controller. The control-measurement solutions, realized on the laboratory stand are described: contact and contactless techniques of sway angle of a payload sensing, including a dynamic vision system employed to detect the sway angle of a rope, and a single camera based stereovision system used for identifying a map of the crane workspace and planning the non-collision trajectory of a payload. The rest of this paper is organized as follows. Section two describes the method of designing an anti-sway fuzzy control scheme. The software-hardware equipment and control-measurement solutions of laboratory stand, and experimental results are presented in section three. Section four delivers the final conclusions.

2. Fuzzy scheduling control scheme design

2.1. Poles assignment-based fuzzy scheduling scheme design

The model of a planar crane dynamic system (Figure 1) is assumed in the form first- and second-order discrete-time transfer functions representing the relations between crane speed and input function (1), and sway angle of a payload and crane speed (2), where a_0 , a_1 , b_0 , b_1 , c_0 , and d_0 are the parameters which vary in relation to the rope length l and mass of a payload m .

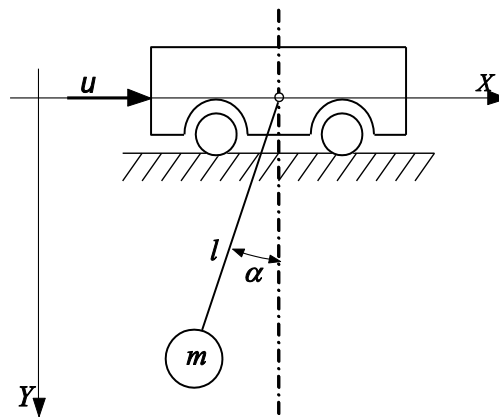


Figure 1. Planar crane system.

$$\frac{\dot{X}(z)}{U(z)} = \frac{d_0}{z + c_0} \quad (1)$$

$$\frac{\alpha(z)}{\dot{X}(z)} = \frac{b_1 z + b_0}{z^2 + a_1 z + a_0} \quad (2)$$

The control system consists of two proportional controllers k_1 and k_2 for crane position and speed, and first-order discrete-time controller of payload sway angle with coefficients denoted q_0 , q_1 and s_0

(Figure 2). The closed-loop control system transfer function can be presented as (3), where $\mathbf{z} = [z^4, z^3, z^2, z^1, z^0]$, \mathbf{R} is the vector of controllers parameters and their multiplications (4), \mathbf{S} is the matrix consisting of crane model's parameters (5), and T_s is a sample time.

$$\frac{\alpha(z)}{X_r(z)} = \frac{k_1 k_2 d_0 (b_1 z^2 + (b_1 s_0 + b_0)z + b_0 s_0)}{z^5 + zSR} \quad (3)$$

$$\mathbf{R} = [1, k_2, q_0, q_1, s_0, k_1 k_2, k_2 s_0, k_1 k_2 s_0]^T \quad (4)$$

$$\mathbf{S} = \begin{bmatrix} a_1 + c_0 - 1 & \begin{pmatrix} a_0 - a_1 + \\ c_0(a_1 - 1) \end{pmatrix} & \begin{pmatrix} c_0(a_0 - a_1) \\ -a_0 \end{pmatrix} & -a_0 c_0 & 0 \\ d_0 & d_0(a_1 - 1) & d_0(a_0 - a_1) & -d_0 a_0 & 0 \\ 0 & 0 & -d_0 b_1 & d_0(b_1 - b_0) & -d_0 b_0 \\ 0 & -d_0 b_1 & d_0(b_1 - b_0) & d_0 b_0 & 0 \\ 1 & a_1 + c_0 - 1 & \begin{pmatrix} a_0 - a_1 + \\ c_0(a_1 - 1) \end{pmatrix} & \begin{pmatrix} c_0(a_0 - a_1) \\ -a_0 \end{pmatrix} & -a_0 c_0 \\ T_s d_0 & T_s d_0 a_1 & T_s d_0 a_0 & 0 & 0 \\ 0 & d_0 & d_0(a_1 - 1) & d_0(a_0 - a_1) & d_0 a_0 \\ 0 & T_s d_0 & T_s d_0 a_1 & T_s d_0 a_0 & 0 \end{bmatrix}^T \quad (5)$$

By assuming the stable poles z_f for closed-loop control system we obtain the Diophantine equation (6), where $\mathbf{p} = [p_4, p_3, p_2, p_1, p_0]^T$ is the vector of coefficients of desired characteristic equation of closed-loop transfer function.

$$z^5 + zSR = \prod_{f=1}^5 (z - z_f) = z^5 + zp \quad (6)$$

Therefore, the controllers parameters can be derived from the equations system expressed as follows:

$$SR = p \quad (7)$$

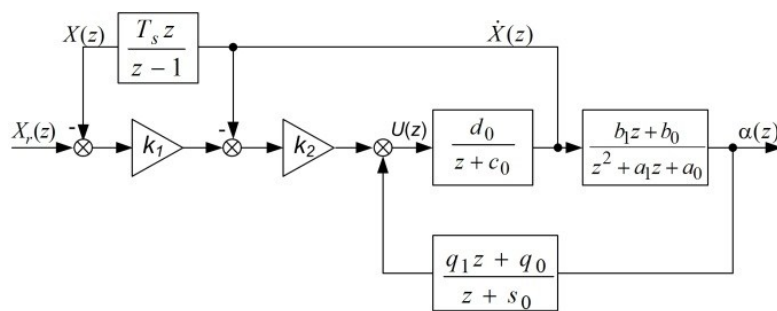


Figure 2. Discrete-time crane control system.

Assuming, that parameters of a model and coefficients of a desired closed-loop characteristic equation are the real numbers, the equation (7) has at least one vector of real roots among three possible solutions. The fuzzy interpolation control scheme can be expressed as a set of controllers determined at N operating points selected within the ranges of scheduling variables $[l_{min}, l_{max}]$ and $[m_{min}, m_{max}]$. Hence, the rule base is a set of N rules expressed as follows:

$$R_k: \text{IF } l \text{ is } \mathbf{A}_i \text{ and } m \text{ is } \mathbf{B}_j \text{ THEN } \mathbf{K}_k = \mathbf{K}(l_i, m_j) \quad (8)$$

where $k = 1, 2, \dots, N$, $\mathbf{K}_k = [k_1, k_2, q_0, q_1, s_0]^T$ is the rule output, and $\mathbf{K}(l_i, m_j)$ is the vector of controllers parameters determined at operating point (l_i, m_j) corresponding to the midpoints of membership functions of fuzzy sets \mathbf{A}_i and \mathbf{B}_j .

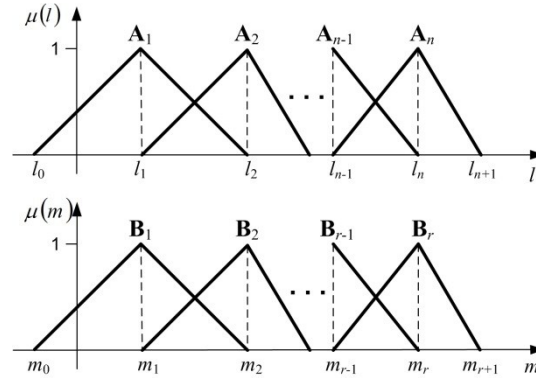


Figure 3. Triangular membership functions specified for rope length and mass of a payload.

The fuzzy scheduler design is based on the following assumptions. The n and r fuzzy sets \mathbf{A} and \mathbf{B} correspond to the triangular-shaped (Figure 3) membership functions (9-10) with centre points $[l_1, l_2, \dots, l_n]$ and $[m_1, m_2, \dots, m_r]$ distributed within the intervals $[l_{\min}, l_{\max}]$ and $[m_{\min}, m_{\max}]$ of scheduling variables.

$$\mu_{A_i}(l) = \max \left(\min \left(\frac{l - l_{i-1}}{l_i - l_{i-1}}, \frac{l_{i+1} - l}{l_{i+1} - l_i} \right), 0 \right) \quad (9)$$

where: $l_{i-1} \leq l_i \leq l_{i+1}$, $i = 1, 2, n$.

$$\mu_{B_j}(m) = \max \left(\min \left(\frac{m - m_{j-1}}{m_j - m_{j-1}}, \frac{m_{j+1} - m}{m_{j+1} - m_j} \right), 0 \right) \quad (10)$$

where: $m_{j-1} \leq m_j \leq m_{j+1}$, $j = 1, 2, \dots, r$.

The number of rules $N = n \cdot r$ depends on all combinations of fuzzy sets $\{\mathbf{A}_i, \mathbf{B}_j\}$ specified for scheduling variables l and m . The output of fuzzy scheduler is a vector $\mathbf{K}(l, m)$ of controllers parameters interpolated for $l \in [l_{\min}, l_{\max}]$ and $m \in [m_{\min}, m_{\max}]$:

$$\mathbf{K}(l, m) = \sum_{k=1}^N w_k \cdot \mathbf{K}_k \quad (11)$$

where w_k is a weight of k -rule calculated as follows:

$$w_k = \mu_{A_i}(l) \cdot \mu_{B_j}(m) \quad (12)$$

For the above assumptions, the fuzzy controller design involves to select the number of membership functions specified for scheduling variables and determine distribution of their center points within the assumed intervals.

2.2 Interval arithmetic-based design of a fuzzy scheduler

The requirements of the control performances can be represented by the interval vector of characteristic equation coefficients \mathbf{P} corresponding to the desired region of closed-loop poles defined as the intervals:

$$[z_f^-, z_f^+] = \{z_f \in \mathbb{R} \mid z_f^- \leq z_f \leq z_f^+\} \quad (13)$$

where: $f = 1, 2, \dots, 5$.

Thus, the desired closed-loop system characteristic polynomial can be presented as follows:

$$P(z) = \prod_{f=1}^5 (z - [z_f^-, z_f^+]) = z^5 + zP \quad (14)$$

where \mathbf{P} is the vector of closed-loop characteristic polynomial coefficients intervals:

$$\mathbf{P} = \llbracket p_4^-, p_4^+ \rrbracket, \llbracket p_3^-, p_3^+ \rrbracket, \dots, \llbracket p_0^-, p_0^+ \rrbracket^T \quad (15)$$

The control quality requirements for parameters varying within intervals $[l_{\min}, l_{\max}]$ and $[m_{\min}, m_{\max}]$ are satisfied if the closed-loop system characteristic polynomial coefficients lie within desired interval vector \mathbf{P} :

$$\mathbf{S}(l, m) \cdot \mathbf{R}(l, m) \in \mathbf{P} \quad (16)$$

where the vector $\mathbf{R}(l, m)$ consists of controller gains $\mathbf{K}(l, m)$ interpolated by fuzzy inference system according to the formula (7). In practice, it is enough to check the condition (16) for the most hazardous operating points which correspond to the crossover points of membership functions:

$$l_c = (l_i + l_{i+1})/2, m_c = (m_j + m_{j+1})/2 \quad (17)$$

The procedure of designing the fuzzy gain scheduling system involves to identify parameters of crane dynamic model at operating points $\{l_{\min}, m_{\min}\}$, $\{l_{\min}, m_{\max}\}$, $\{l_{\max}, m_{\min}\}$ and $\{l_{\max}, m_{\max}\}$. The bounds of scheduling variables intervals are assumed as the centre points of triangular membership functions of fuzzy sets denoted \mathbf{A}_1 , \mathbf{A}_n , \mathbf{B}_1 and \mathbf{B}_r . Assuming desired regions of closed-loop poles for those operating points, the vector of controller gains are determined according to (7) for the midpoints of those regions. Hence, the initial rule base (18) is created for $n = r = 2$ fuzzy sets defined in the universes of l and m .

$$\begin{aligned} R_1 : & \text{IF } l \text{ is } \mathbf{A}_1 \text{ and } m \text{ is } \mathbf{B}_1 \text{ THEN } K_1 = K(l_1, m_1) \\ R_2 : & \text{IF } l \text{ is } \mathbf{A}_1 \text{ and } m \text{ is } \mathbf{B}_r \text{ THEN } K_2 = K(l_1, m_r) \\ R_3 : & \text{IF } l \text{ is } \mathbf{A}_n \text{ and } m \text{ is } \mathbf{B}_1 \text{ THEN } K_3 = K(l_n, m_1) \\ R_4 : & \text{IF } l \text{ is } \mathbf{A}_n \text{ and } m \text{ is } \mathbf{B}_r \text{ THEN } K_4 = K(l_n, m_r) \end{aligned} \quad (18)$$

Selecting the number of sample points N_l and N_m within the scheduling variables intervals $[l_{\min}, l_{\max}]$ and $[m_{\min}, m_{\max}]$, the fuzzy scheduler design is realized in a two-stage process through firstly incrementing the sample points l_i ($i = 1, 2, \dots, N_l$) within the interval $[l_{\min}, l_{\max}]$, and in the next stage incrementing sample points m_j ($j = 1, 2, \dots, N_m$) within the range $[m_{\min}, m_{\max}]$. In the first stage, assuming $n = 2$, the sample points of rope length are incremented from l_{\min} . At each iteration the n is incremented and the sample point l_i is temporarily assumed as the centre point of membership function of fuzzy set \mathbf{A}_{n-1} . The parameters of a crane's model are linearly interpolated based on the parameters identified at operating points $\{l_{\min}, m_{\min}\}$, $\{l_{\min}, m_{\max}\}$, $\{l_{\max}, m_{\min}\}$ and $\{l_{\max}, m_{\max}\}$ for the operating points corresponding to l_i and l_c , where l_c is the crossover point between neighboring membership functions \mathbf{A}_{n-2} and \mathbf{A}_{n-1} . The condition (16) is tested for each crossover point l_c to check that coefficients of closed-loop characteristic polynomial lie in a restricted region for gains interpolated by the fuzzy system. If any violation of the condition (16) occurs, then the new membership function is specified with the center point l_{i-1} tested successfully in the previous iteration. The iterative procedure for selecting center points of membership functions distributed within the interval $[l_{\min}, l_{\max}]$ is realized in the following steps:

1. Increment i and n , and assume that the current value l_i is a center point l_{n-1} of temporary membership function of fuzzy set \mathbf{A}_{n-1} .
2. Approximate the parameters of crane's model at operating points $\{l_{n-1}, m_1\}$ and $\{l_{n-1}, m_r\}$ through linear interpolation between operating points $\{l_{\min}, m_{\max}\}$ and $\{l_{\max}, m_{\max}\}$. Specify for those two

points desired regions of closed-loop poles and calculate the controllers gains $\mathbf{K}(l_{n-1}, m_1)$ and $\mathbf{K}(l_{n-1}, m_r)$ for midpoints of those regions according to (7).

3. Add to the rule base (19) the two new rules:

R_{k+1} : IF l is \mathbf{A}_{n-1} and m is \mathbf{B}_1 THEN $\mathbf{K}_{k+1} = \mathbf{K}(l_{n-1}, m_1)$

R_{k+2} : IF l is \mathbf{A}_{n-1} and m is \mathbf{B}_r THEN $\mathbf{K}_{k+2} = \mathbf{K}(l_{n-1}, m_r)$

where $k = N$, and N is equal to the number of rules in the previous iteration.

4. Linearly interpolate the system parameters for operating points $\{l_c, m_1\}$ and $\{l_c, m_r\}$, and test the condition (16) at those operating points, for vectors of gains $\mathbf{R}(l_c, m_1)$ and $\mathbf{R}(l_c, m_r)$ interpolated by a fuzzy system.
5. If the condition (16) is satisfied, remove the rules created in the step 3, decrement n , and repeat the steps from 1 to 4 until $i = N_i$.
6. If any violation of the condition (16) occurs, then decrement i , and specify the new triangular membership function for a fuzzy set \mathbf{A}_{n-1} with the center point l_n defined at l_{i-1} , which has satisfied the condition (16) at previous iteration. Remove rules created in the step 3, and repeat the steps 2-3, to create the rules for a new set \mathbf{A}_{n-1} . Repeat the steps 1-5 until $i = N_i$.

The similar procedure is used to find the number of membership functions for scheduling variable m . Assuming initial number of fuzzy sets $r = 2$, the sample points m_j are incremented starting from m_{min} :

1. Increment j and r , and assume that current value m_j is a center point m_{r-1} of temporary membership function of a fuzzy set \mathbf{B}_{r-1} .
2. Linearly interpolate the parameters of crane model at the operating points $\{l_1, m_{r-1}\}$, $\{l_2, m_{r-1}\}$, ..., $\{l_n, m_{r-1}\}$. Specify desired regions of closed-loop poles for those operating points, and calculate the controllers gains $\mathbf{K}(l_1, m_{r-1})$, $\mathbf{K}(l_2, m_{r-1})$, ..., $\mathbf{K}(l_n, m_{r-1})$ according to (7).
3. Add to the rule base the following n rules:
 R_{k+1} : IF l is \mathbf{A}_1 and m is \mathbf{B}_{r-1} THEN $\mathbf{K}_{k+1} = \mathbf{K}(l_1, m_{r-1})$
 R_{k+2} : IF l is \mathbf{A}_2 and m is \mathbf{B}_{r-1} THEN $\mathbf{K}_{k+2} = \mathbf{K}(l_2, m_{r-1})$
 ...
 R_{k+n} : IF l is \mathbf{A}_n and m is \mathbf{B}_{r-1} THEN $\mathbf{K}_{k+n} = \mathbf{K}(l_n, m_{r-1})$
4. Test the condition (16) for operating points corresponding to the crossover points (17) of membership functions of fuzzy sets $\mathbf{A}_1, \mathbf{A}_2, \dots, \mathbf{A}_n$, and \mathbf{B}_{r-2} and \mathbf{B}_{r-1} .
5. If the condition (16) is satisfied, remove the rules created in the step 3 and remove fuzzy set \mathbf{B}_{r-1} , decrement r , and repeat the steps from 1 to 5 until $j = N_m$.
6. If any violation of the condition (16) occurs, then decrement j , and specify the new fuzzy set \mathbf{B}_{r-1} with the center point $m_{r-1} = m_{j-1}$ of triangular-shaped membership function. Remove rules created in the step 3 and repeat the steps 2-3, to create the rules for new set \mathbf{B}_{r-1} . Repeat the steps from 1-5 until $j = N_m$.

The iterative procedure results in selecting the suitable number of membership functions and their distribution within scheduling variables intervals. Nevertheless, the crane's model parameters should be identified at selected operating points and the condition (16) should be tested again for all crossover points of membership functions $\{l_c, m_c\}$ to confirm the robustness of a control scheme.

3. Control system prototyping for laboratory scaled overhead travelling crane

3.1 The crane control equipment and measurement solutions

In this section the laboratory stand and control-measurement solutions addressing the problems of anti-sway crane control, non-collision path planning and trajectory tracking are presented. The overhead crane consists of motions mechanisms driven by DC motors. The control system can be configured using different platforms: PAC system with RX3i controller or PC with I/O board and Matlab software (Figure 4). The measurement systems implemented on the laboratory scaled overhead crane, are based on contact and contactless techniques. The position and speed of crane motion

mechanisms are measured using incremental encoders. The sway angle of a payload can be measured using three methods: i) encoder used to measure the rotary angle of the fork-bottomed arm embracing a rope, ii) Hall-effect magnetic field sensors UV-3HF mounted on the hook assembly to measure its deflection from the equilibrium, iii) the intelligent camera type of Sony XCI V3 installed under the trolley and directed to the rope. In the last technique, the vision software integrated with the embedded system, allows to extract the specified rectangular region of snapshot with the isolated rope straight line, and determine the angle between the detected rope edge and parallel line of image height [10]. The strain-gauge based measurement system is employed to identify the mass of payload.

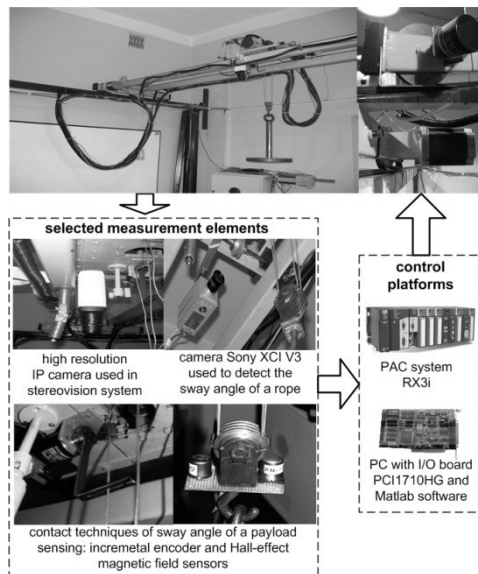


Figure 4. The control-measurement equipment of laboratory scaled overhead crane

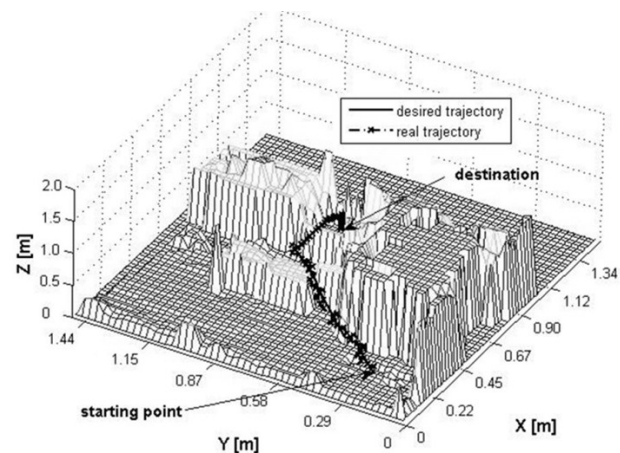


Figure 5. The map of 3D crane workspace, desired trajectory determined using A-star algorithm, and real trajectory of a payload transferred by a crane.



Figure 6. The epipolar transformation of stereo pair of images.

Moreover, the stereovision based method with a single camera was implemented on the laboratory stand to identify a map of transportation workspace. The camera is installed under the trolley, and used to capture the image pair at different position of the crane. The three-dimensional map of crane workspace is obtained through rectification of images leading to obtaining epipolar lines, dense disparity map calculation, and determination of coordinates for each of the image pixel. The example of a crane workspace map for a rectified image pair (Figure 6) is presented in figure 5, where the non-collision path of a payload between two points was designed using well known A-star graph search

algorithm with the objective function defined based on the average velocities of crane motion mechanisms [20], and compared with trajectory obtained in experiment.

3.2 Examples of experiments

The method of designing the fuzzy gain scheduling anti-sway crane control system, which is described in section 2, was tested on a laboratory scaled overhead crane. The control scheme was designed for scheduling variables intervals $[l_{min}, l_{max}] = [0.8, 2.2]$ m and $[m_{min}, m_{max}] = [10, 90]$ kg. The parameters of a crane model (1-2) were identified using OE method for the operating points: $\{l_{min}, m_{max}\}$, $\{l_{min}, m_{min}\}$, $\{l_{max}, m_{max}\}$, $\{l_{max}, m_{min}\}$. The regions of desired poles were assumed as:

$$z_f = [\exp((- \omega_n \mp \omega_n(1 - \xi))T_s)] \quad (19)$$

where sample time and a parameter determining the width of desired poles interval were assumed as $T_s = 0.1$ s and $\xi = 0.9$, respectively. Taking into account constraints of a control system imposed by limitation of crane speed and controlling signal, and assuming that reference signal $x_r = 1$ m should be obtained with tolerance ± 0.02 m of crane and payload position, the closed-loop poles interval specified for $\omega_n \in [2.06, 2.95]$ rad/s corresponds to the expected settle time interval [5.5, 6.5] s. The iterative procedure resulted in designing the fuzzy scheduler with six rules, and membership functions with centre points at $l = \{0.8, 1.5, 2.2\}$ m and $m = \{10, 90\}$ kg. The control algorithm was written in the form of structured text on the PAC system. Figures 7-9 show the examples of experiments carried out on the laboratory object for operating points corresponding to the centre points (Figure 7-8) and crossover points (Figure 9) of membership functions.

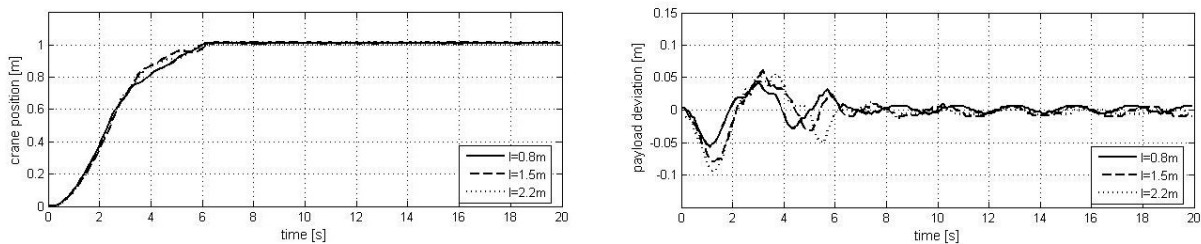


Figure 7. Crane position and payload deviation - experiments conducted for $m = 10$ kg.

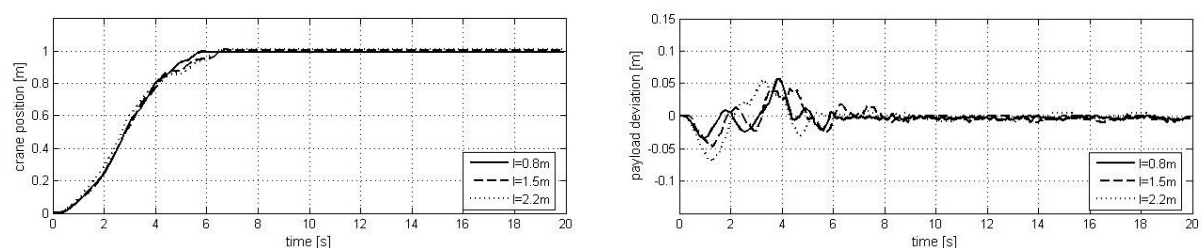


Figure 8. Crane position and payload deviation - experiments conducted for $m = 90$ kg.

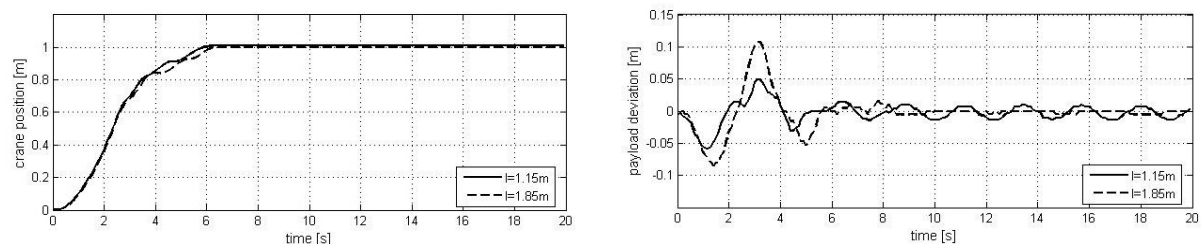


Figure 9. Crane position and payload deviation - experiments conducted for $m = 50$ kg.

The experiments conducted on the laboratory scaled overhead crane shown satisfactory results. The settle time for experiments conducted for operating points lying within intervals $[0.8, 2.2]$ m and $[10, 90]$ kg was between 5.5 and 6.5 seconds, and reduction of payload deflection was in the expected range ± 0.02 m. Thus, the results of the experiments prove the effectiveness of the proposed method for designing a fuzzy logic-based gain scheduling control scheme.

Figure 10 presents the comparison of system responses in three experiments carried out at operating point corresponding to the midpoints of intervals $[0.8, 2.2]$ m and $[10, 90]$ kg. The first experiment (solid line) was conducted with fuzzy control scheme satisfying the desired condition for closed-loop system characteristic polynomial coefficients that resulted in determining the center points of triangular shaped membership functions at $l = \{0.8, 1.5, 2.2\}$ m and $m = \{10, 90\}$ kg. The crane position and reduction of payload deflection with tolerance ± 0.02 m is achieved at about 6 s. In the next experiments, carried out for fuzzy system interpolating the controllers parameters within interval $[0.8, 2.2]$ m (dashed line), and for linear closed-loop control system designed at operating point $\{2.2$ m, 10 kg $\}$ (dotted line), the condition (16) has been violated for desired region of closed-loop system poles (19) resulting in control system performances deterioration: settle time in both experiments is 6.8 s and 7.1 s, respectively.

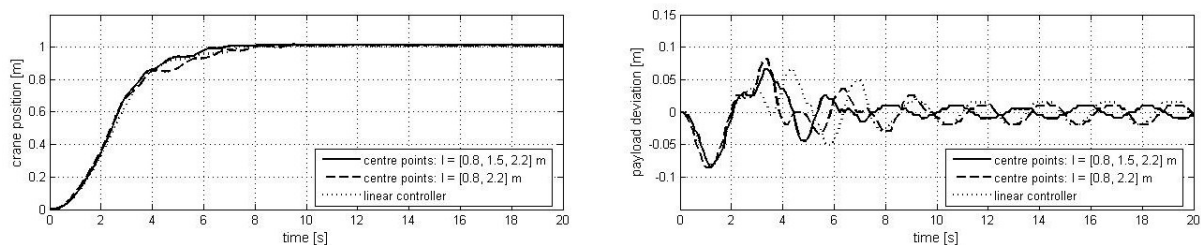


Figure 10. Crane position and payload deviation - experiments conducted for $l = 1.5$ m and $m = 50$ kg.

4. Conclusions

The fast, precise and safe transfer of goods in crane operations requires a control application to solve the problems, including shortest and non-collision trajectory planning and limitation of payload oscillations. This paper delivers solutions which can be employed to create such complex control systems. The control-measurement equipment elaborated for laboratory overhead crane are presented. The contact and contactless techniques were implemented for measuring the sway angle of a payload, including a dynamic vision system based on a camera detector of sway angle of a rope. The single camera based stereovision system was elaborated to identify a crane workspace map, which has been successfully tested to design the non-collision trajectory of a payload.

The novelty approach to crane dynamic system modeling and the fuzzy robust control scheme design utilizing interval analysis of closed-loop system characteristic polynomial coefficients is proposed in the form of the iterative procedure for selecting a suitable number of fuzzy sets and membership functions parameters distribution within the expected ranges of scheduling variables. Good control performances obtained during the experiments carried out on the laboratory scaled device proved that the proposed solution can be applicable using software-hardware equipment's used frequently in the industrial practice

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