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PARAMETER IDENTIFICATION OF A ROBOT ARM USING GENETIC ALGORITHMS

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Abstract

An identification method for inverse dynamics of a robot arm based on genetic algorithms (GA) is considered. It is shown that GAs are able to find robot parameters effectively even if the robot has low resolution position encoders. It is possible because the method only requires position feedback and there is no need to find out the speed and acceleration of the links that usually can only be done through finite differences calculations that cause dramatic errors during identification. The effectiveness of the algorithm is demonstrated on the example of parameter identification of the real robot PUMA 560 (for second and third links).

Keywords: identification, genetic algorithms, robot, PUMA 560.

1. Introduction

An industrial robot is a high non-linear dynamic system because of interconnections between links. That is why a simple decentralised control cannot successfully deal with the case of fast movements of the end-effector and high requirements to the quality of the tracking. Therefore, it is necessary to apply some advanced control algorithms to provide high quality tracking control. There are two different methodologies. The first one is to design a robust controller using minimum information about the dynamics (MRAC [1], Sliding Mode Control [2]). However, these techniques allow to compensate non-linear effects only after the tracking error has occurred. The second methodology – Computed Torque Control [3] – is based on the use of the inverse dynamic model of the robot that is as close as possible to the real one. The method allows to use prior information such as desired acceleration during the tracking and configuration of the robot, to predict and feed-forward counteract the various non-linear effects to avoid any tracking error. The main drawback of the second approach is the need for an accurate plant model. There are many identification techniques that can be divided into two categories. The first one includes the methods that are based on the classic presentation of the robot dynamics (i.e. Newton–Euler formulation) [4, 5, 15]. The methods related to the second one are based on the use of universal approximators such as fuzzy logic and neural network methodologies [6, 7]. Although these methods seem to be very attractive because in the ideal case they allow to model the dynamic effects even 'bad'-modeled, for example, friction. However, a huge number of search parameters and absence of physical meaning of the last ones lead to great difficulties in the case of practical implementation. Since the classic methods take the robot configuration into account the number of search parameters is considerably smaller than in the case of universal approximators. However, the need of calculation of speed and acceleration through finite differences, because usually only position signal is available for measurements, makes these methods insufficient for practical implementation due too big calculation errors caused by sampling of output signal of the position encoder. That is why we proposed an identification method [8] based on genetic algorithms that searches parameters of the classic dynamic model of the robot but only uses position signal for identification. Furthermore, the practical application of the GA-based method for parameter identification of the robot PUMA 560 (see *Fig. 1*) that found the wide spreading in industry is considered in detail. As it is the first attempt of application of the approach for the real robot let consider the application of the method for the robot type usually used at testing of different identification methods – two links articulated robot arm or in our case – the second and third links of the robot PUMA 560.

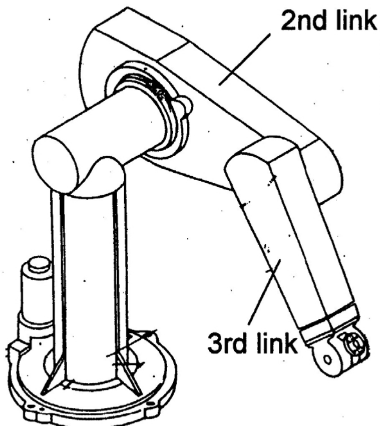

Fig. 1. The robot PUMA 560

2. Dynamic Model of the Robot

In general form the dynamic model for a robot has the following form:

$$D\,(q)\,\ddot{q} + h\,(q, \dot{q}) = \tau, \tag{1}$$

where q is $n \times 1$ vector of joint positions; $\dot{q}$ is $n \times 1$ vector of joint velocities; $\ddot{q}$ is $n \times 1$ vector of joint accelerations; $D(q)$ is the $n \times n$ inertia matrix; $h(q, \dot{q})$ is the

$n \times 1$ vector of Coriolis, centrifugal and gravitational torques; τ is the $n \times 1$ vector of joint torques, n is number of degree of freedom. On the basis of Newton–Euler formulation and using the Denavith–Harterberg notation (modified form) [16] the dynamic model of PUMA 560 (for second and third links) has been derived. More detailed information about complete dynamic model of the robot PUMA 560 can be found in [10].

$$\begin{bmatrix} \tau_2 \\ \tau_3 \end{bmatrix} = \begin{bmatrix} f_1 + 2 f_3 cq_3 - 2 f_4 sq_3 & f_2 + f_3 cq_3 - f_4 sq_3 \\ f_2 + f_3 cq_3 - f_4 sq_3 & f_1 \end{bmatrix} \cdot \begin{bmatrix} \ddot{q}_2 \\ \ddot{q}_3 \end{bmatrix} + \begin{bmatrix} - f_3 sq_3 \dot{q}_3^2 - 2 f_3 \dot{q}_2 \dot{q}_3 sq_3 - f_4 \dot{q}_3^2 cq_3 - 2 f_4 \dot{q}_3 \dot{q}_2 cq_3 \\ f_3 \dot{q}_2^2 sq_3 + f_4 \dot{q}_2^2 sq_3 \end{bmatrix} + \begin{bmatrix} - f_5 gc\,(q_2 + q_3) + f_6 gs\,(q_2 + q_3) + f_8 gsq_2 - f_9 gcq_2 \\ - f_5 gc\,(q_2 + q_3) + f_6 gs\,(q_2 + q_3) \end{bmatrix}. \tag{2}$$

Here, g is the gravity acceleration; sq_i and cq_i are sine and cosine of correspondent joint positions; $f_1 - f_9$ – independent robot parameters that have to be identified. The form of these parameters is following:

$$\begin{aligned} f_1 &= J_{m_2} k_3^2 + I_{zz_3} + m_3 x_3^2 + m_3 y_3^2; \\ f_2 &= I_{zz_3} + m_3 x_3^2 + m_3 y_3^2; \\ f_3 &= m_3 x_3 a_3; \\ f_4 &= m_3 y_3 a_3; \\ f_5 &= m_3 x_3; \\ f_6 &= m_3 y_3; \\ f_7 &= J_{m_3} k_2^2 + I_{zz_2} + m_2 x_2^2 + m_2 y_2^2 + m_3 a_3^2 + I_{zz_3} + m_3 x_3^2 + m_3 y_3^2; \\ f_8 &= m_2 y_2; \\ f_9 &= m_2 x_2 + m_3 a_3; \end{aligned} \tag{3}$$

where m_i is link mass; J_{m_i} is motor inertia; k_i is gear ratio; I_{zz_i} is link's moment of inertia about the z axis of the frame i; x_i and y_i are coordinates of link's centers of gravity in the frame i; a_3 is Denavith–Harterberg parameter (distance between z_2 and z_3 axes), i is number of link. Note, as it can be seen from (2), for the control there is no need to find the real parameters of the robot (mass, center of mass, etc.). It is necessary to find independent parameters f_i, $i = 1, 9$ because they directly influence the dynamic behaviour of the robot. As these parameters have been identified they can be used in design of the controller based on the Computed Torque Control approach (CTC controller). Scheme of the computed torque control method is presented in *Fig. 2*.

In *Fig. 2* $\widehat{D}\,(q)$ and $\widehat{h}\,(q, \dot{q})$ are the estimated inertia matrix and the estimated matrix of Coriolis, centrifugal and gravitational torques, respectively, $\ddot{q}_{des}$ is $n \times 1$

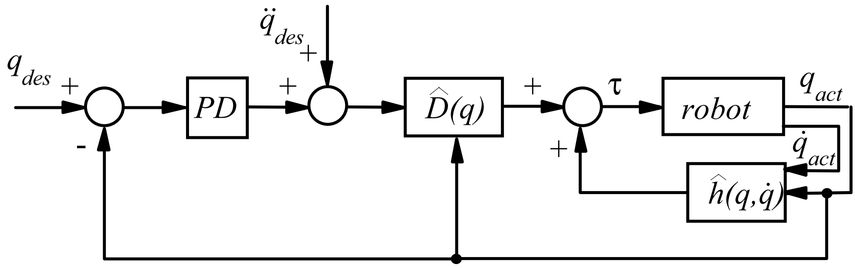

Fig. 2. The computed torque control scheme

vector of desired acceleration of the joints, q_{des} is $n \times 1$ vector of desired position of the joints, q_{act} is $n \times 1$ vector of actual position of the joints, $\dot{q}_{\text{act}}$ is $n \times 1$ vector of actual speed of the joints.

3. Parameter Identification of the Robot

It is possible to say that a model represents the model of the robot if both the robot and the model following the same trajectory have the same tracking errors in each moment of time. Thus, the robot will be well identified if parameters f will be found that the model with these parameters accurately repeats position feedback of the robot for the same trajectory. So, it is possible to identify the robot parameters only on the basis of information about position response during the tracking. Genetic algorithms represent a good approach for a search method that can find the parameters of the model that produce the same form of position response in time as the robot for the same trajectory.

3.1. Genetic Algorithms

In the last years GAs have been found as a very powerful method for the solution of engineering problems. Genetic algorithms search the solution in the whole searching region, and as GA is not a gradient search method, they 'suffer' less from the local minimum. Therefore, this method has more chances to find the global solution of the problem than other methods. GA is a stochastic search method and operates on a population of potential solutions applying the principle of survival of the fittest to produce better and better approximations to a solution [9]. The scheme of the genetic search is presented in *Fig. 3*. At the beginning of the computation a number of individuals (the population) are randomly initialized from a range defined by the user. The objective function is then evaluated for these individuals. The first/initial generation is produced. If the optimization criteria are not met, the creation of a new generation starts. Individuals are selected according to their fitness

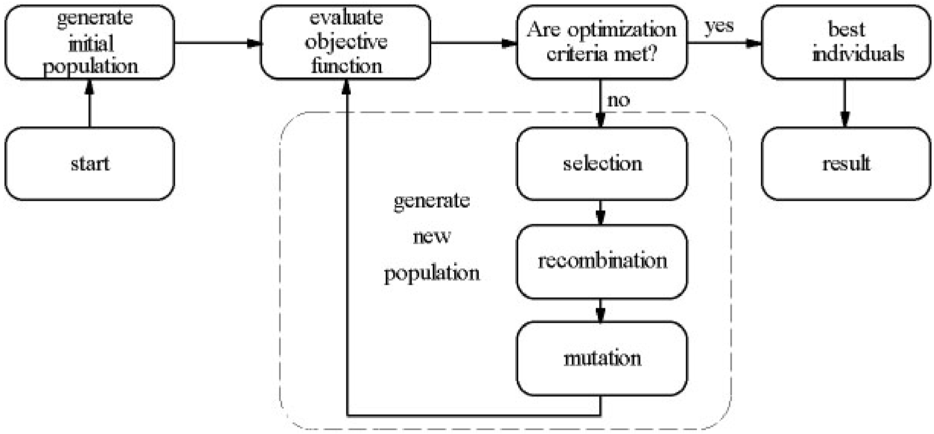

Fig. 3. Genetic search

for the production of offspring. Parents are recombined to produce offspring. All offspring will be mutated with a certain probability. The fitness of the offspring is then computed. The offspring are inserted into the population replacing the parents, producing a new generation. This cycle is performed until the optimisation criteria are met.

3.2. GA-Based Identification Procedure for the Robot Inverse Dynamics

On the basis of the above considerations the GA-based identification algorithm has the following steps:

1. The robot with decentralized P-control follows some trajectories.
2. The sequence of the tracking errors as a function of time is created.
3. An initial population of parameters of the inverse dynamic model is randomly generated from the pre-defined range.
4. Each member of the population is evaluated by using an objective value.
5. Then GA procedure occurs, i.e. each member of the population is encoded in a binary chromosome and the following consequences of the genetic operations are performed: selection – recombination – mutation.
6. As a result, a new population appears. After a given number of the epochs the result will be coded in the chromosome with the least objective value.

For implementation of the above algorithm it is necessary:

1. Creating the model of the robot with actuators and control system.
2. Choosing the objective function.
3. Choosing the tracking trajectory.
4. Choosing initial range for generation of the first population.

5. Choosing parameters of the GA (crossover's probability, mutation's probability and so on).

3.3. *The Plant Model*

On the basis of the equations of a DC motor and using (2) and (3), the model of the robot actuated by DC motors with the control system, that contains current PI-controller in the low level and P-controller in position control loop, has been derived. A block diagram of the robot's model with the control system is presented in *Fig. 4*.

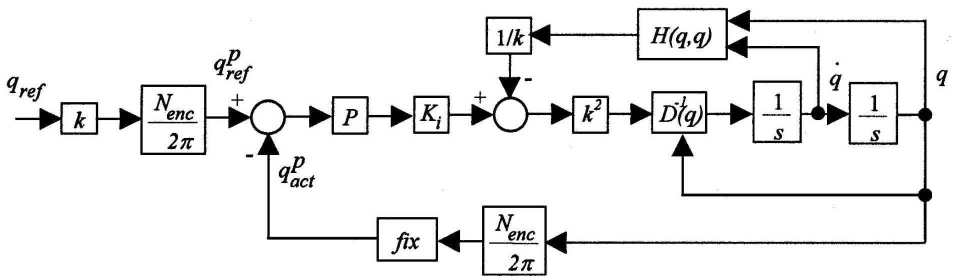

Fig. 4. Diagram of the robot drive with the control system

In *Fig. 4*:

q_{ref}	–	the 2×1 vector of the reference joint position;
q^{p}_{ref}	–	the 2×1 vector of the reference motor shaft position in pulses;
k	–	the 2×1 vector of gear ratio;
P	–	the 2×1 vector of coefficients of the P-controller;
N_{enc}	–	the 2×1 vector of number of encoder pulses per revolution;
K_i	–	the 2×1 vector of the motor gain;
$D^{-1}(q)$	–	the 2×2 inverse inertia matrix derived form (2);
$H(q, \dot{q})$	–	the 2×1 vector of Coriolis, centrifugal, gravitational forces and friction forces derived from (2);
s	–	Laplace operator;
q^{p}_{act}	–	the actual position of the motor shaft in pulses;
fix	–	a function that rounds a number towards zero,
q	–	$n \times 1$ vector of actual position of the joints
$\dot{q}$	–	$n \times 1$ vector of actual speed of the joints.

Note, in most robots the mechanical time constant of the drive is much bigger than the electrical one. That is why transients of the current control loops can be neglected [5]. As a result, in the model the output of the position controller can be considered as the motor torque (apart from dimensions).

3.4. Objective Function

A sum of the squared error between the tracking error of the robot and the tracking error of the model during a movement along the same trajectory can serve as an objective function of the model's correspondence to the accurate model of the robot because a smaller value of the squared error corresponds to a more accurate model of the robot.

$$Y = \sum_{j=1}^{M} \sum_{i=1}^{N} \left(e_{ij}^{r} - e_{ij}^{m}\right)^{2} . \quad (4)$$

In (4):

Y – the objective function;
e_{ij}^r – tracking error of j-th joint of the robot in i-th sample time (in pulses);
e_{ij}^m – tracking error of j-th joint of the model in i-th sample time (in pulses);
N – number of the sample data;
M – number of the robot joints.

3.5. Reference Trajectory

It is necessary to choose such a trajectory in which both mutual influences of the links and inertial features of the links should be noticeable. That is why the sinusoidal trajectory with different amplitudes and frequencies for each joint seems to be the most suitable as a reference signal.

3.6. Initial Range for Generation of the First Population

It is obvious that accuracy and convergence of any search algorithm depends on the choice of initial conditions of the search. The nearer the initial conditions to the solution, the more accurate and the quicker the convergence of the searching. Because the physical meaning of searching parameters and the robot sizes are known we can approximately estimate the range the robot's parameters belong to. It is known that the mass of the PUMA 560 is 53 kg. It is possible to suppose that the second link's mass belongs to the range $m_2 \in [5 \div 25]$ kg because, at least, the second link contains two DC motors and m_2 cannot be more than a half of the robot mass, analogously, $m_3 \in [1 \div 10]$ kg. Furthermore, we take into account the sizes of the robot and the supposition that center of mass has to lie in the middle part of the link, i.e.

$$r \in [l_{\min}/2 \div l_{\max}/2], \quad (5)$$

where r is a coordinate of center of mass, $l_{\min}$ and $l_{\max}$ are minimal and maximal possible coordinates of center of mass's in the link's frame, respectively. Thus, on the basis of measurements of sizes of the robot, coordinates of centers of mass x_2, y_2, x_3, y_3 and parameter a_3 can belong to following ranges:

$$x_2 \in [-0.12 \div 0.25]\ \text{m}; \qquad y_2 \in [-0.07 \div 0.07]\ \text{m};$$
$$x_3 \in [-0.04 \div 0.04]\ \text{m}; \qquad y_3 \in [0 \div -0.25]\ \text{m};$$
$$a_3 \in [0.3 \div 0.5]\ \text{m}.$$

The moment of inertia of the motors can be obtained from the motor data, but also for such a type of motor (a DC brush motor) and for such an input motor power (approximately 200W) the inertia usually belongs to the range $J_m \in [1 \cdot 10^{-4} \div 1 \cdot 10^{-4}]\ \text{kg} \cdot \text{m}^2$. The link's moment of inertia can be estimated taking the link's mass and the link's sizes into account , i.e. $I_{zz_2} = [0 \div 1.69]\ \text{kg} \cdot \text{m}^2$, $I_{zz_2} = [0 \div 0.625]\ \text{kg} \cdot \text{m}^2$. So, on the basis of the above suppositions and using (3) it is possible to calculate the initial ranges of the unknown robot parameters. A minimal value of the range corresponds to the minimal possible value that gives a combination of terms in the expression for robot's parameter calculation. In the case of a maximal value it is the opposite. For example, $f_{9_{\min}} = m_{2_{\max}} \cdot x_{2_{\min}} + m_{3_{\min}} \cdot a_{3_{\min}}$. Thus, the initial ranges for the unknown robot parameters are the following:

$$f_1 \in [0.28 \div 4.07]\ \text{kg} \cdot \text{m}^2; \qquad f_2 \in [0 \div 2.33]\ \text{kg} \cdot \text{m}^2;$$
$$f_3 \in [-0.2 \div 0.2]\ \text{kg} \cdot \text{m}^2; \qquad f_4 \in [-1.25 \div 0]\ \text{kg} \cdot \text{m}^2;$$
$$f_5 \in [-0.4 \div 0.4]\ \text{kg} \cdot \text{m}; \qquad f_6 \in [-2.5 \div 0]\ \text{kg} \cdot \text{m};$$
$$f_7 \in [2.23 \div 17.95]\ \text{kg} \cdot \text{m}^2; \qquad f_8 \in [-1.75 \div 1.75]\ \text{kg} \cdot \text{m};$$
$$f_9 \in [-2.7 \div 11.25]\ \text{kg} \cdot \text{m}.$$

3.7. Control Parameters of Genetic Algorithms

On the basis of the simulation results and using guidelines presented in [11] and [12], the following methods and parameters of the genetic operations were found the most suitable for the above task:

1. Binary representation of the chromosome;
2. Number of individuals in a population is 20;
3. Rank-based fitness assignment with the selection pressure 2.0;
4. Single-point crossover with probability 0.6;
5. Number of subpopulations is 4 or more;
6. Complete net migrate structure;
7. Migration rate is 0.3;
8. Generation gap is 0.94, i.e. less offspring than individuals in a population is produced.
9. Number of generations is 40.

4. Experiment

The GA-based identification algorithm was implemented in MATLAB with the help of the Genetic Algorithms Toolbox. The model of the robot was realised in a MEX-file to facilitate the speed of calculation. Results of the computer simulation study of the identification method [13] have shown that the last one is able to search unknown robot parameters with the acceptable accuracy. However, it is more interesting to test the applicability of the method for parameter identification of the real robot.

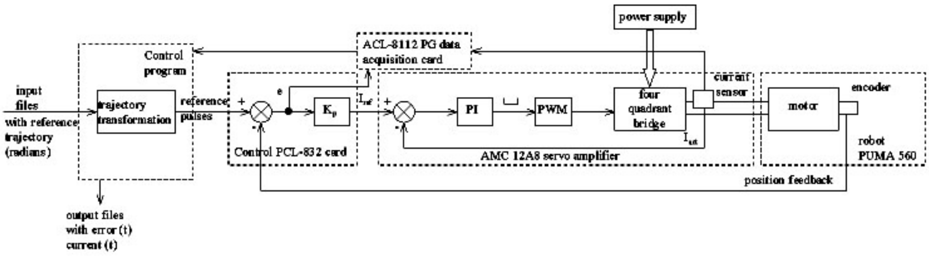

Fig. 5. The experimental plant

4.1. *The Experimental Plant*

The control scheme of one degree of freedom of the experimental plant is presented in *Fig. 5*. The reference trajectories from the file are loaded into the control program that transforms the reference values into ones expressed in pulses. The last ones are fed in the PCL-832 control card that generates the required number of pulses. The summing circuit of the card determines the difference between the number of the command pulses and the ones from the servo motor encoder device. The computed result is fed into the P-controller of the card. Its output is the input for the AMC 12A8 servo amplifier (reference current for the current control loop) that contains internal current loop with analog PI-controller, PWM circuit and four-quadrant transistor bridge. The output of the servo amplifier is a command voltage for the servomotor. Approximately every 0.7 ms the control program reads through the ACL-8112PG data acquisition card the actual armature current from the current sensor of the servo amplifier as well as the actual position error from the summing circuit of the control card PCL-832. After completion of the desired movement the control program writes the collected data into the file.

4.2. *The Experimental Results*

The following trajectory has been chosen as a reference signal for second and third links of the robot, correspondingly,

$$q_{\text{ref2}} = -\frac{\pi}{4} + \frac{\pi}{4}\cos\left(\frac{2\pi t}{T}\right),$$
$$q_{\text{ref3}} = \frac{\pi}{4} - \frac{\pi}{4}\cos\left(\frac{2\pi t}{T/2}\right), \tag{6}$$

where T is time of the movement that in the experiment was equal to 3.65 sec. It is necessary to note that the initial configuration of the robot corresponded to the zero configuration according to the Denavith–Harterberg notation. After the test movement the following sequences of the tracking errors (*Fig.* 6, *Fig.* 7) and currents (*Fig.* 8, *Fig.* 9) were collected.

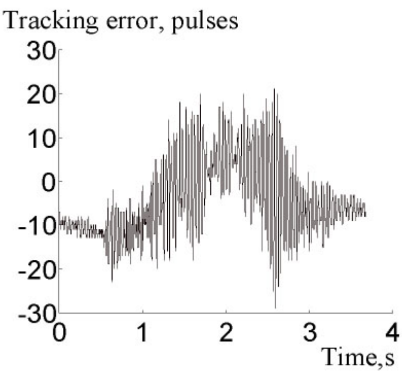

Fig. 6. The tracking error of the second link's motor

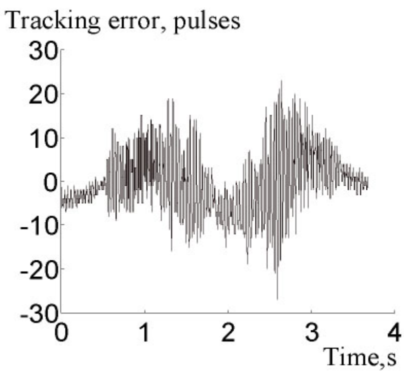

Fig. 7. The tracking error of the third link's motor

As it can be seen from the above figures, the form of the current function and the one of the tracking error of the corresponding motor are mostly the same. That is why in the model we can neglect time constant of the current loop because of it is too small (i.e. assume that actual current is equal to the reference current of the loop) and the back electromotive voltage because of the mechanical time constant is much bigger than the electrical one. On the basis of the current's and the tracking error's data the actual gain of the P-controller can be calculated. As it can be seen in *Fig.* 6, the noticeable oscillations with frequency 27–32 Hz are presented in the tracking error of the links that are caused by flexibility of the joints and the presence of the backlash in the gearboxes. These oscillations are not caused by the influence of the inertial parameters of the robot, therefore, we can filter them to get clear information about the identified object. The tracking errors of both links after filtration are presented in *Fig.* 10, *Fig.* 11.

After the robot tracking errors have been collected, the identification procedure based on the suppositions B-G of part 3 can be carried out. For parameters of the model such as gear ratios, encoder resolutions, friction constants see Appendix.

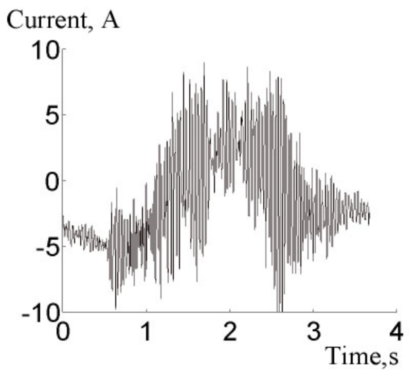

Fig. 8. The armature current of the second link's motor

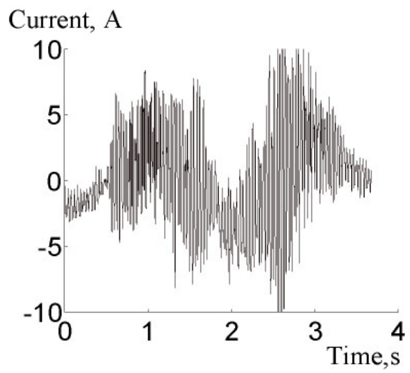

Fig. 9. The armature current of the third link's motor

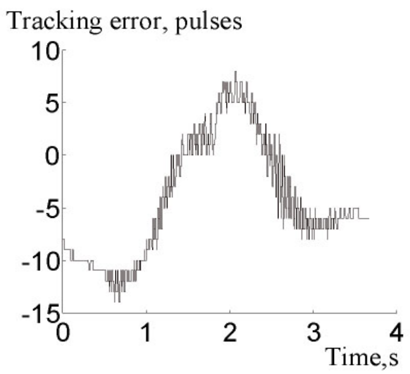

Fig. 10. The tracking error of the second link and the one of the third link

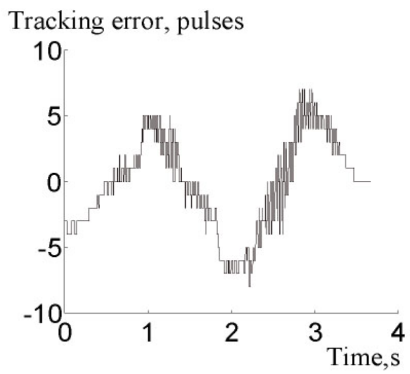

Fig. 11. The tracking error of the second link after filtration

Note that the values of the gear ratio and encoder resolution are available from the robot catalogue. The values of the friction constant were derived from the test of the servomotors [14]. If the last ones are unknown, then they have to be included as unknown parameters in the dynamic model of the robot.

In *Fig. 12*, *Fig. 13* the tracking errors of some models from the initial population are presented. As a rule, the best value of the objective function in the first generation is about 38000–45000 pulses^2. Usually during the identification this value decreases to 23000-25000 pulses^2. In *Fig. 14*, *Fig. 15* the tracking errors of the best model after identification are presented. As it can be seen the tracking errors of the model are mostly the same as the real robot's ones (range of errors, form of the curves). Thus, it shows that the Genetic Algorithms based identifica-

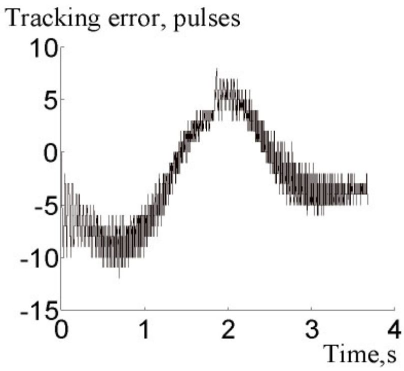

Fig. 12. The tracking error of the second link and the one of the third link

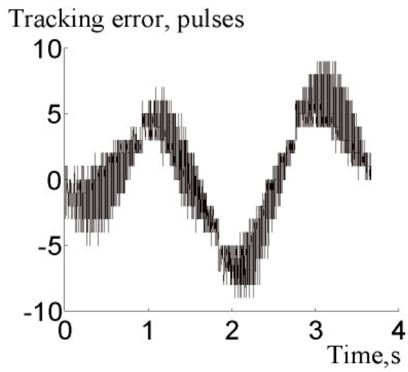

Fig. 13. The tracking error of the second link of best model from the initial population

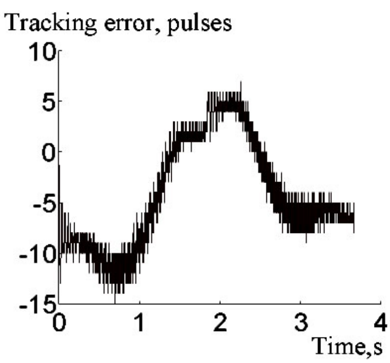

Fig. 14. The tracking error of the second link and the one of the third link

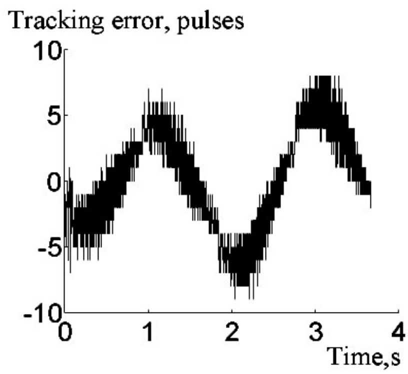

Fig. 15. The tracking error of the second link of the best model after identification

tion method is able to find such parameters of the robot's model that with these parameters dynamically behaves like the real robot.

Values of the inertial parameters of the robot $f_1 - f_9$ derived from the identification are the following: $f_1 = 1.68$ (alteration $\pm 10\%$), $f_2 = 1.39$ (alteration $\pm 21\%$), $f_3 = -0.29$ (alteration $\pm 80\%$), $f_4 = -1.4$ (alteration $\pm 30\%$), $f_5 = -0.08$ (alteration $\pm 16\%$), $f_6 = -1.94$ (alteration $\pm 14\%$), $f_7 = 6.67$ (alteration $\pm 11\%$), $f_8 = 0.06$ (alteration $\pm 40\%$), $f_9 = 10.2$ (alteration $\pm 3\%$), where alteration means variation in results after series of identification procedures. The presence of the relatively big alteration values can be explained by the fact that in the range of the tracking errors $[-10 \div +10]$ pulses, the error in one pulse (because position feedback from the encoder is always an integer number) plays the significant role that is expressed in different combinations of values of inertial parameters. The difference between found values of the last ones and values that are known from the literature is explained by the fact that during the experiment the robot had a drill-tool in the end-effector that was considered as a part of the third link.

5. Conclusion

The identification method for inverse dynamics of the robot based on genetic algorithms (GA) was considered. It was shown that the GAs are able to search robot parameters effectively even if the proportional control with low resolution position encoders is available for the robot control. It is possible because the method requires only position feedback and there is no need to find out speed and acceleration of the links that usually can be done only through finite differences calculations that cause dramatic errors during identification. The effectiveness of the algorithm was demonstrated on the example of parameter identification of the real robot PUMA 560 (for second and third links). It was shown that Genetic Algorithms based identification method was able to find such parameters of the robot's model that with these parameters dynamically behaves like the real robot. It is necessary to note, that one of the most attractive features of the method is that the approach is practically independent of the resolution of the encoder. Because the task of the procedure is to find such a combination of the inertial parameters that the model of the robot containing these parameters could repeat the tracking response of the robot along the same trajectory with a given accuracy of the encoder. So, if such parameters are found then it is not important what the accuracy of the identified parameters is because it is important that such a CTC can be designed on the basis of the obtained model which can provide tracking with desired accuracy (± 1 encoder pulse). The proposed approach has been applied for the off-line identification of the robot model. However, during the working movements of the robot the mass of the carrying load and its inertial parameters have an influence on the robot model. Therefore, these parameters have to be identified on-line. The following procedure can be proposed for on-line GA-based identification of the robot model. At first, in off-line mode inertial parameters of the robot are identified. Since they remain constant, in the on-line mode only parameters of the load are identified, namely, mass of the load and moments of inertia. The process can be divided into three stages. At the first stage (100–200 ms) the reference sequence of the tracking errors of the robot is collected. During this stage parameters of the load, included in the CTC controller as other parameters of the robot model, have some constant values, for example, half of the maximum possible values. At the second stage GA-based identification of the load parameters is carried out. Note that the number of the searched parameters is smaller than at off-line identification of the rest robot parameters and the number of the collected sample data is smaller as well than at off-line identification.

That is why the time needed for the identification is significantly smaller than the one needed for the off-line identification. So, approximately, within 3–4 sec it is possible to obtain identified parameters of the load. As a result, at the third stage the identified parameters are taken into account in parameters of the CTC controller. It is necessary to note that the speed of the identification completely depends on resources of the host computer. So, the method can be a time-consuming procedure that is considered as a disadvantage of the algorithm. For example, the described identification procedure carried out on a personal computer (Pentium, 200 MHz, 32 Mbyte RAM) required about a half an hour to perform the search. However, impetuous progress in the field of computer technique is able to significantly reduce this disadvantage in the near future.

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Appendix

The robot parameters.

$$\text{Kfr-visc}_2 = 0.817e-3 \text{ (Nsec/rad)}, \quad \text{Kfr-visc}_3 = 1.38e-3 \text{ (Nsec/rad)};$$
$$\text{Kfr-stat}_2 = 0.124 \text{ (N)}, \quad \text{Kfr-stat}_2 = 0.146 \text{ (N)};$$
$$k_2 = 107.8,\ k_3 = -53.7; \quad \text{Nenc}_2 = 800 \text{ (pulse/rev)},$$
$$\text{Nenc}_3 = 1000 \text{ (pulse/rev)}.$$

In the list of parameters.

Kfr-stat is the static friction of the correspondent motor, Kfr-visc is the gain of the viscous friction of the corresponding motor.

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