

# OPTIMIZATION OF THE ROBOT SPACE TRAJECTORY BY USING KINEMATICS, DYNAMICS, INTELLIGENT DAMPER AND PROPER NEURAL NETWORK

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**Abstract:** *In the robotics field one of the more important is the optimization of the space trajectory of the tool center point (TCP) without the undesired frequencies of the vibrations. The paper shows one new optimizing method by controlling the robots space trajectory by using the direct and inverse kinematics, direct and inverse dynamics, desired optimal Fourier spectrum and proper neural network. The proper neural network was established after the assisted research of the dynamic behavior, by trying to use some known networks type. The better solution of the neural network design, for solving the inverse kinematics and direct dynamics problems with the final goal of obtaining quickly the convergence process of the space trajectory and the Fourier target spectrum with the minimum errors without some of the frequencies of the spectrum was established by using the LabVIEW proper instrumentation, after the assisted research of all network parameters like the hidden layer data, amplifier gain, time delay and position in the network structure, recurrent links and number of neurons in each of all three used layers. The Sigmoid Bipolar Hyperbolic Tangent with Time Delay and Recurrent Links SBHTNN (TDRL) neural network type was proposed and used. The complex controlling of the space trajectory was made by using three neural networks of the same type: the first one to solve the inverse kinematics problem, the second for the direct dynamics problem by using some output data from the first one and the third one to establish the magnetorheological damper current intensity. All obtained results were verified by applying the simulation with LabVIEW instrumentation. Finally we obtained one optimal complex controller that can optimize the kinematics, dynamics and vibrations with trajectory errors smaller than 2%. The proper neural network, the controller design, the results and the virtual LabVIEW instrumentation could be used in many other mechanical applications.*

**Key words:** *space trajectory, inverse kinematics, direct dynamics, intelligent damper, neural network, virtual LabVIEW instrumentation.*

## 1. INTRODUCTION

In the programming and controlling the TCP space trajectory of the robots, the trajectory errors and vibrations are of great importance. The present paper tries to obtain the minimum of the errors by solving the inverse kinematics, the direct dynamics and Fourier spectrum with the desired frequencies by using the proper neural network.

The paper shows one new design of the one complex controller concerning the dynamic behavior controlling of the robots with the final goal to obtain the minimum space trajectory errors and one movement of the robot end-effector with only desired vibration. In many applications it is needed the extreme precision of the movement and it is necessary to avoid the resonance frequencies of the other devices what work close to the robot.

In many applications where the extreme precision was necessary like the space driving or the guidance, the accuracy of taking the image, the accuracy of talking or

to hearing, will be applied the neural networks. A first wave of interest in neural networks was the introduction of simplified neurons by McCulloch and Pitts in 1943. Many other applications of the neural networks have tried to develop this field, most notably being Teuvo Kohonen, Stephen Grossberg, James Anderson and Kunihiko Fukushima [1–10].

The inverse kinematics was used to control the end-effector trajectory. The inverse kinematics solutions obtained by geometrical method are more difficult to find, when the robot degrees of freedom increase. Inverse kinematics solutions are obtained usually by geometrical method, numerical method with known outputs and with neural network optimization [1–5]. The neural network method for obtaining the real solutions of the inverse kinematics in the actual research does not show the simulation results and the optimization of the errors. In the paper it was proposed for optimization of the trajectory error, after applying the inverse kinematics control, one new method with proper neural network what using three layers, many time delay blocks and recurrent links. All layers used the sensitive sigmoid bipolar hyperbolic tangent function types to take in consideration the input data influences to the internal coordinates  $q_i$  in both di-

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Fig. 1. The used set up for the assisted research.

reactions of the movement [6–18]. The last layer is used to adapt the number of data vector with the needed number of outputs. The optimal errors have been obtained by applying the back propagation proper method, the bipolar sigmoid hyperbolic tangent sensitive function, the multiple time delay and the recurrent links and some of the results of the presented research, like the amplifier gain, hidden layer target data, step of the time delay, etc. Neural network are composed of simple elements operating in parallel, like a biological nervous system. As in nature, the connections between elements largely determine the network function. You can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Neural network have been trained to perform complex functions in various fields including pattern recognition, identification, classification, speech, vision and control systems.

## 2. EXPERIMENTAL SETUP

The experimental set up contains the following components, see Fig. 1: didactical arm type robot; the electromagnetic exciter type 11075 from RFT Germany; connector type CB-68 LP from National Instruments USA; acquisition board type PCI 6024E from National Instruments USA; frequency generator type POF-1 from KABID Poland; amplifier for frequency generator type LV 102 from MMF Germany to generate the force stimulus; personal computer from Taiwan; inductive displacement transducer type 16.1 IAUC Romania; tachogenerator for velocity; Hottinger apparatus type KWS/T5 from Germany; proper MRD and some virtual LabVIEW instrumentation.

## 3. MATHEMATICAL MODELLING

The complex mathematical model was written in the matrix form and contains the robot kinematics and dynamics equations, damper dynamic behavior equation, neural network used model SBHT(TDRL) and DC matrix form equation shown in Eqs. (1). The mathematical model was used for designing the virtual LabVIEW instrumentation and the complex controller of the robot DC motors. The mathematical model contains some parameters that were used for the assisted research of the proper neural network with the final goal to choose the optimal values for the numbers of the neurons in the hidden layer, amplifier gain, step of the time delay, position in the neural scheme to apply the time delay and recurrent links. The damper equations have the nominated parameters established after the assisted experimental research and validation of the mathematical model for the used magnetorheological damper.

$$\begin{aligned} (r)_i^0 &= (r)_{i-1}^0 + [D]_{i-1}^0 (r)_{i-1}^{i-1}; \\ [D]_{i-1}^0 &= [D]_1^0 [D]_2^0 \dots [D]_{i-1}^{i-2}; \end{aligned} \quad (1)$$

$$(r)_1^0 = \begin{pmatrix} 0 \\ 0 \\ l_1 \end{pmatrix}; (r)_2^0 = \begin{pmatrix} 0 \\ 0 \\ l_1 + l_2 \end{pmatrix}; (r)_3^0 = \begin{pmatrix} c_1 s_2 l_3 \\ s_1 s_2 l_3 \\ l_1 + l_2 + c_2 l_3 \end{pmatrix};$$

$$(r)_4^0 = \begin{pmatrix} c_1 s_2 l_3 + (c_1 c_2 s_3 + c_1 s_2 c_3) l_4 \\ s_1 s_2 l_3 + (s_1 c_2 s_3 + s_1 s_2 c_3) l_4 \\ l_1 + l_2 + c_2 l_3 + (-s_2 s_3 + c_2 c_3) l_4 \end{pmatrix}.$$

$$\begin{pmatrix} F \\ M \end{pmatrix} = \begin{bmatrix} z_u & 0 \\ 0 & z_v \end{bmatrix} \begin{pmatrix} D_{\omega_i} (F_k^i + f(i)) \\ D_{\omega_i} M_k^i \end{pmatrix} - \text{diag} \left[ \text{sign} \frac{v_i^i}{|v_i^i|} m_{\omega_i}, \text{sign} \frac{\omega_i^i}{|\omega_i^i|} J_{\omega_i} \right] \cdot \begin{pmatrix} (\alpha_{i,0}^i + [\hat{\omega}_{i,0}^i]^2) (r_i^i) \\ (\epsilon_{i,1}^i + [\hat{\omega}_{i,1}^i] (\omega_{i,1}^i)) \end{pmatrix} + \begin{bmatrix} z_u & 0 \\ 0 & z_v \end{bmatrix} \cdot \begin{pmatrix} [G_{i,1}^i] (\hat{b}_{i,1}^i) (D_{\omega_i} (F_k^i + f(i)) - \text{diag}^{(0)} \left[ \text{sign} \frac{v_i^i}{|v_i^i|} m_{\omega_i} \right] \cdot [D_{\omega_i} (\alpha_{i,0}^i + [\hat{\omega}_{i,0}^i]^2) (r_i^i)]) \\ [G_{i,2}^i] (\hat{b}_{i,2}^i) (D_{\omega_i} (F_k^i + f(i)) - \text{diag}^{(0)} \left[ \text{sign} \frac{v_i^i}{|v_i^i|} m_{\omega_i} \right] \cdot [D_{\omega_i} (\alpha_{i,0}^i + [\hat{\omega}_{i,0}^i]^2) (r_i^i)]) \end{pmatrix}$$

$$f(i) = c_0 (x' - y') + k_0 (0.003 - y) + 100(x - 0.002) + \alpha x,$$

$$y' = \frac{1}{c_0 + c_1} [\alpha x + c_0 x' + k_0 (0.003 - y)],$$

$$z' = -74 |x' - y'| |z| |z|^{n-1} - 1047(x' - y') |z|^n + 40000(x' - y'),$$

$$\alpha(i) = 0.9i^3 + 1.1i^2 + 0.9i + 0.9,$$

$$c_0(i) = 60i^3 - 70i^2 + 19i + 7,$$

$$c_1(i) = -i^3 + 30i^2 + 5i + 1000$$

$$k_0(i) = 200i^3 + 100i^2 + 100i + 300$$

$$\delta = 50 \sin(10\pi + 0.21) + 1.1 \sin(18\pi + 0.31) +$$

$$+ 1.4 \sin(30\pi + 0.62).$$

$$n_1 = \left[ w^1 + \underbrace{tcg_1}_{p_2} \cdot \epsilon_1 \right] (p - a_2 (t - p_3 + 1)) + (b_1 + \epsilon_1),$$

$$a_1 = \frac{p_4 (1 - e^{-n_1})}{1 + e^{-n_1}},$$

$$\epsilon_1 = t_1 - a_1,$$

$$n_2 = \left[ w^2 + \underbrace{tcg_2}_{p_5} \cdot \epsilon_2 \right] (a_1 (t - p_6 + 1)) + (b_2 + \epsilon_2),$$

$$a_2 = \frac{p_7 (1 - e^{-n_2})}{1 + e^{-n_2}},$$

$$\epsilon_2 = t_2 - a_2,$$

$$q_i = p_8 (a_2 - \epsilon_f),$$

$$\epsilon_{pos} = t_3 - r_i,$$

$$n_3 = \left[ w^3 + \underbrace{tcg_3}_{p_5} \cdot \epsilon_{pos} \right] (q_i) + (b_3 + \epsilon_{pos}),$$

$$a_3 = \frac{p_9 (1 - e^{-n_3})}{1 + e^{-n_3}},$$

$$\epsilon_f = t_2 - a_3.$$

$$(U_m) = \frac{L}{K_m} \cdot (M) + \left( \frac{R_a}{K_m} \cdot [J_{red}] + L_a \cdot \frac{b}{K_m} \cdot \frac{d}{dt} (\omega_m) + (R_a \cdot \frac{b}{K_m} + K_e) \cdot (\omega_m) \right).$$

The last equation is the matrix equation of the dynamic behavior of the robots DC motors, where the DC motors tension matrix contains the variable tensions that where established after applying the complex controller, where: the  $r_i^0$  is the matrix form of the absolute position

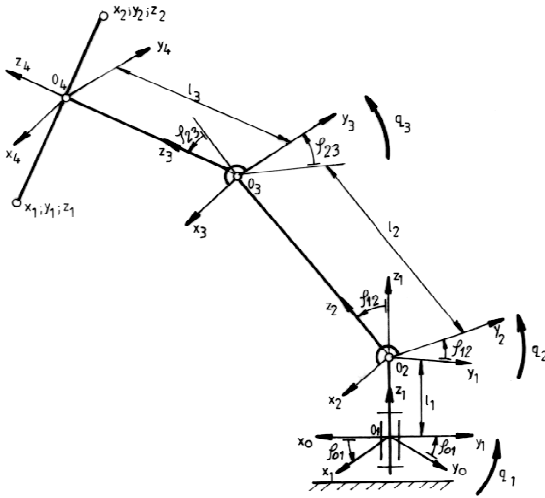


Fig. 2. Structural-cinematic schema of the researched diactural robot.

control; vector of the  $i$  joint;  $r_{i-1}^0$  – matrix form of the absolute position of the  $i-1$  joint;  $r_i^{i-1}$  – matrix form of the relative position vector between the  $i$  and  $i-1$  joints;  $D_{i-1}^0$  – coordinates transform matrix from the  $i-1$  joint to the base Cartesian system;  $l_i$  – lengths of each robot modules;  $c_i, s_i$  – cosines and sinus trigonometric functions of the relative angle and relative  $q_i$  robot coordinate between  $i$  and  $i-1$  robot bodies;  $f(i)$  – magnetorheological damper force vs. electrical intensity  $i$ ;  $F$  – active forces matrix in a Cartesian fixed system;  $M$  – active moment matrix in a Cartesian fixed system;  $z_u$  – joint bodies matrix;  $D_{i-1}^i$  – transfer matrix between  $i-1$  and  $i$  body;  $F_R$  – resistant force matrix;  $M_R$  – resistant moments matrix;  $m_i$  – mass matrix of  $i$  body;  $J_{gi}^0$  – inertial tensor matrix of  $i$  body;  $a_{i,0}^i$  – absolute dual acceleration matrix in a  $i$  body Cartesian system;  $\omega_{i,0}^i$  – non symmetric absolute angular velocity matrix in a  $i$  body Cartesian system;  $\varepsilon_{i,i-1}^i$  – angular relative acceleration matrix in a  $i$  body Cartesian system;  $\omega_{i,i-1}^i$  – angular relative velocity in a  $i$  body Cartesian system;

$B^\wedge$  – modified arm forces matrix;  $x$  and  $y$  – primary, respectively the secondary displacement variables of the magnetorheological damper (MRD);  $z$  – internal history dependency variable of the (MRD);  $k_0, k_1$  – non linear internal rigidity of the (MRD) depending of the current intensity  $i$ ;  $c_0$  and  $c_1$  – internal viscous damping parameters of the (MRD);  $\alpha$  – internal parameter that has non linear evolution and depends on the magnetic variable field (electrical intensity); parameter  $\beta$  characterize the gain of increasing of the damping force versus velocity;  $x_0$  is the perturbation displacement;  $\delta$  – is the hysteresis parameter;  $tcg$  – teaching gain of the neural network;  $p$  – inputs,  $w$  – weights,  $b$  – bias;  $p_1$  – the assisted research proposed parameters about  $p_1$  – number of neurons;  $p_2$  – first teaching gain;  $p_3$  – step of the first time delay;  $p_4$  – the first sensitive function gain;  $p_5$  – second teaching gain;  $p_6$  – step of the proportional error control of the second time delay;  $p_7$  – second sensitive function gain;  $p_8$  – the magnify gain of the output data;  $p_9$  – the third sensitive function gain;  $U_m$  – electrical tension matrix;  $J_{red}$  – inertial tensor matrix reduced at the motor axes;  $\omega_m$  – angular motor velocity matrix;  $L_\omega, R_\omega, K_m, K_e, b$  – DC motor parameters.

#### 4. DESIGN OF THE COMPLEX CONTROLLER

To perform the TCP space trajectory three neural networks BSHTNN (TDRL) type were used (Fig. 6). We used the first one (Fig. 4) to obtain the increasing of the precision to determine the relative movement when the start and stop points were imposed, by using the inverse and direct kinematics in the neural network with multiple time delay and recurrent links. We used the second one (Fig. 4) to determine the real relative movements in each joint in a dynamic behavior, by using the same type of the neural network and inverse dynamics (determining the active moment in each joints) and direct dynamics (determining the real relative movements and accelerations in each joint). The third one (Fig. 5) was used to perform the Fourier spectrum.

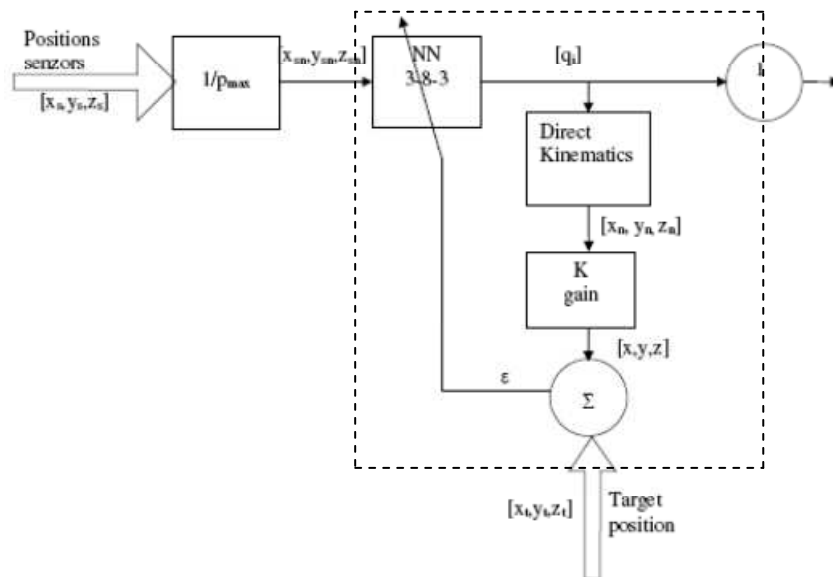


Fig. 3. The first stage of the controller- kinematics controller.

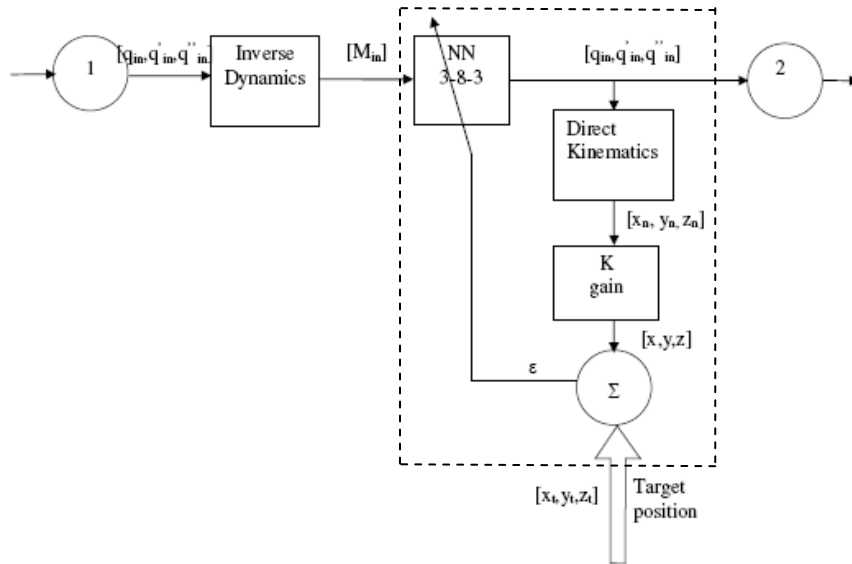


Fig. 4. The second stage of the controller- dynamics controller.

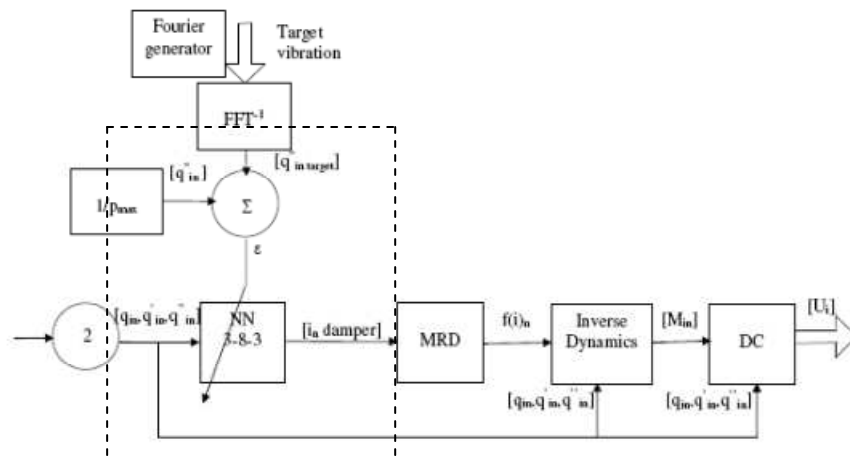


Fig. 5. The third stage of the controller- Fourier spectrum controller.

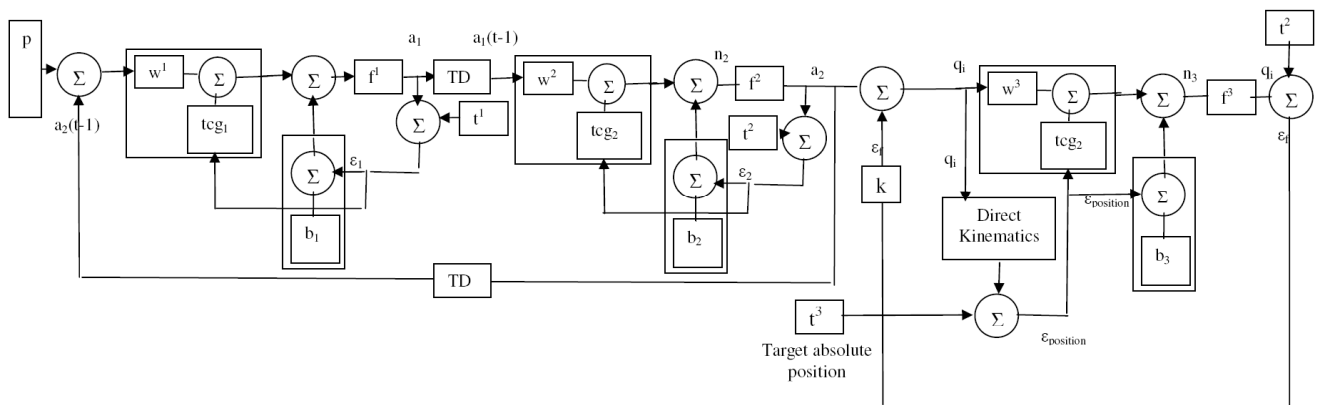


Fig. 6. The complex schema of the proposed proper neural network BSHT(TDRL) type.

## 5. NUMERICAL SIMULATION

The numerical simulation was made by using the proper LabVIEW instrumentation that contains the sixth numerical simulation (VI-s) of the direct kinematics, of the proper used neural network BSHT (TDRL) type, of

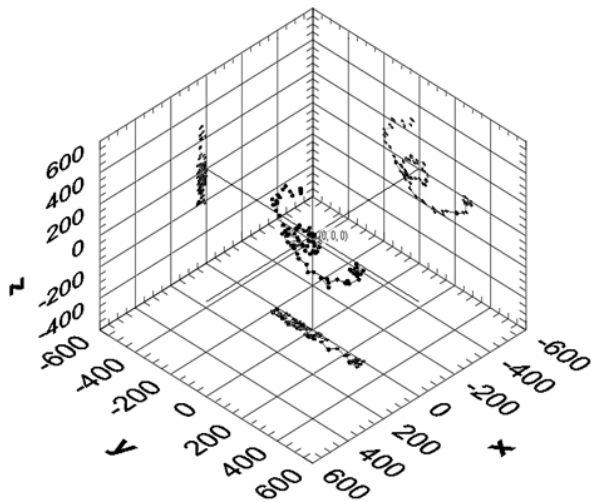


Fig. 7. Numerical simulation of the 3D space trajectory without proposed controller.

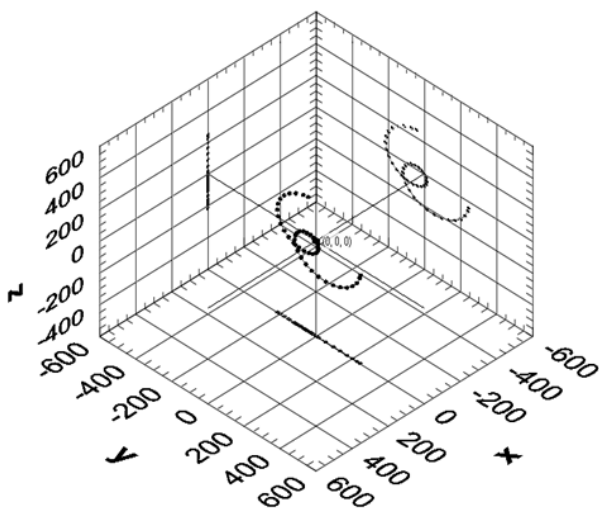


Fig. 8. Numerical simulation with first three frequencies from the Fourier spectrum with filtered magnitude at 0.1 and was applied neural network controlling.

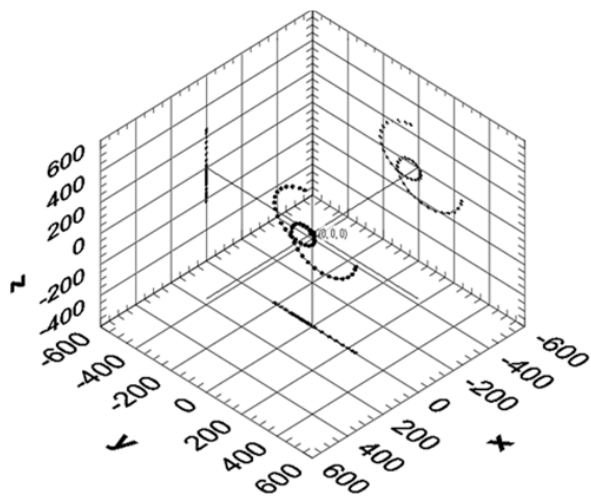


Fig. 9. Numerical simulation of the 3D space trajectory after were decreased the first frequencies magnitude to 0.4 and was applied neural network controlling.

the proper magnetorheological damper, of the proper matrix form of the dynamics behavior and of the DC motor matrix form. All the VI-s work on-line with the possibility to adjusted them to obtain one small errors in the validation research activities when was compared the simulation modeling with the answer data obtained by data acquisition and experimental research (Figs. 7–9). We can see some of these results in the references [12–18]. The numerical simulation tried to show how the space 3D trajectory was changed when the proper neural network was applied to the Fourier spectrum or not, and the cinematic and dynamic data obtained where used by using the proposed complex control of the kinematics, dynamics and Fourier spectrum and the proper neural network.

## 6. DISCUSSION AND CONCLUSIONS

The important goal of the research was to obtain the minimum of the space trajectory errors of the TCP movement by controlling the kinematics, dynamics behavior and Fourier spectrum. The research was achieved in the three ways of the filtering the answer of the robotic complex system. The first one was the cinematic control by using alternatively the direct and inverse cinematic calculus and the proper neural network BSHT (TDRL) type. The second one was the control of the dynamic behavior by using alternatively the inverse and direct dynamic calculus and the same NN. The third one was to decrease the magnitude of some undesired frequencies of the Fourier spectrum or avoiding them by using the proper frequency Fourier generator, the same NN and the intelligent damper system. All research was made by using the proper LabVIEW instrumentation for the numerical simulation and for experimental data acquisition. Some of the realized LabVIEW instruments and some of the results can be used in many other mechanical applications.

The future work will be focused to the research the TCP space movement after applying some known excitation frequencies with the same frequencies and magnitude but in opposite phase for decreasing the undesired magnitude frequencies from the Fourier spectrum [19–26].

The complex controller of the dynamic behavior of the robotic system remains one of the most important things in this future research by applying the new advanced mechatronic devices.

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