UDK: 007.52, 004.032.26
COSATI: 06-04, 14-07

# Advanced Connectionist Control Algorithm for Robotic Compliance Tasks based on Wavelet Network Classifier

Duško Katić, PhD (Eng)[1)]

**In this paper, a new comprehensive intelligent control strategy based on connectionist learning of robotic system uncertainties and wavelet network classification of unknown robot environments is proposed. The proposed wavelet neural network classifies characteristics of environments, determines the control parameters for compliance control and in coordination with basic learning compliance control algorithm reduces the influence of robot dynamic model uncertainties. In order to verify the proposed approach, compliant motion simulation experiments with a robotic arm placed in contact with a dynamic environment are realized. Computer simulation shows that the neural network classification provides a significant force error reduction.**

*Key words*: **robotics, robots, control algorithm, neural network, simulation model, intelligent control.**

## Introduction

MANY manipulation robots nowadays are required to operate in uncertain environments. Thus, the characteristics of the environment can be assumed unknown and significantly change able according to the particular task. For example, in case of using fixed position/force gains for conventional compliance control tasks, these controllers perform satisfactorily when the environment parameters such as stiffness are known. However, the same controllers typically exhibit sluggish response in contact with softer environment and become unstable in contact with stiffer environment. It is evident that in order to overcome these problems, the controller must be capable of adapting its parameters, and possibly its structure, to the changes in the environment parameters and environment model structure. Apart from environmental uncertainties, for some types of robots, uncertainties of robot dynamic model can have high influence on the quality of the robot performances.

In this field of research two crucial problems still remains: 1) how to determine optimal control parameters under uncertain the characteristics of the robot and environment 2) how to deal with nonlinear characteristics of robot and dynamic environment. The previous research papers, however, did not consider these uncertainties and nonlinearities and, thus, the above approaches were limited to specified working conditions which satisfy only certain assumptions. One possible excellent solution would be using learning concept for contact tasks, since robotic performance can be significantly enhance by learning capabilities using a priori low level of information about the model of robot and environment.

With recent extensive research in the area of robot position/force control, various learning algorithms for constrained manipulation have been proposed such as iterative-analytical, tabular and connectionist (neural networks) methods [1]. Neural networks are able to compensate for a wide range of robot uncertainties and to perform excellent association and knowledge generalization. In the application of neural networks in robot contact tasks, two essentially different approaches can be distinguished: one, the aim of which is the transfer of human manipulation skills to robot controllers and the other in which manipulation robot is treated as an independent dynamic system in which learning is achieved through repetition of the working task. The principle of transfer of human manipulation skill is developed in the papers of Asada at all [2, 3]. The approach is based on acquisition of manipulation skills and strategies from human experts and their transfer to the robot controller by learning connectionist structures. The second group of learning methods, based on autonomous on-line learning procedures with the repetition of the working task, is also evaluated through several algorithms [4-9]. The main distinction between these algorithms is in the aim of learning, which is in the first case the on-line modification of the control signal, and in the second the building of internal model of a robotic system.

Previous research, however, did not consider the problem of environment uncertainties specially. Without an adequate knowledge about environment al dynamics, it is not possible to even determine consistent values of nominal trajectory and force or nominal control, not to mention achieving asymptotic stability. In this case, algorithms that identify the type of environment models on-line, could significantly improve the performance of contact task control schemes. As one solution, off-line identification of environment al parameters based on experimental measuring [10] may also result in good system performance with approximate modeling of sufficiently exact robot dynamic environment. But in the case of nonlinear complex models of the environment or uncertain structure of environment model, conventional parameter identification method is not a solution for compliance control synthesis.

[1)] Mihailo Pupin Institute, Volgina 15, 11060 Belgrade

The mentioned facts led to conclusion that, efficient compliance control algorithms have to include new learning features which is necessary for active compensation of system uncertainties and determination of optimal control parameters. In the case of robotic system uncertainties and uncertain parameters and structure of environment model, some intelligent techniques (fuzzy logic, neural networks, genetic algorithms) can be efficiently applied [11-13] for robot control and dynamic environment identification for compliance control tasks.

Results in this paper can be considered as comprehensive connectionist control approach based on an extension and generalization of the approach developed for connectionist control in robot non-contact tasks and contact tasks [14]. The main feature of the proposed hybrid learning control algorithms is integration of multilayer perceptron into some typical non-learning control law along with the integration of wavelet network classifier. The neural network plays the role of a robust learning controller needed to compensate uncertainties of the dynamic model of manipulation robots in contact with dynamic environment. The wavelet network performs the classification of unknown parameters and structure of environment, which is necessary for selecting the appropriate control parameters of basic non-learning compliance control algorithm. Wavelet network classifier was chosen due to better classification properties in comparison with pure multilayer perceptron approach [15]. The wavelet transformation is very suitable for representation of nonstationary signals with brief, high frequency components as signals from robotic force sensors. The connectionist learning and wavelet classification is achieved through off-line and on-line training process along with the process of pattern association and generalization.

The paper is organized as follows: section 2 where, factors affecting contact task performances in stabilizing position/force control algorithms are analyzed, section 3 where, the basic principles of connectionist approach utilized for environment classification purposes and selection of appropriate control parameters are introduced, section 4 where, the proposed approach is verified through simulation experiments and section 5 which concludes the paper.

## Factors affecting task performance in robotic compliance control

In this section, the specific models of robot and environment considered for classification and control purposes are introduced, as well as special non-learning control algorithm for stabilizing position and force based on quality of transient processes [16]. In order to connect the control algorithm and connectionist approach, factors affecting task performance and stability in control algorithms based on classification of unknown dynamic environment are analyzed particularly. The main idea of using wavelet networks for classification of unknown robot dynamic environment can also be efficiently applied for other types of robot contact control algorithms. Since this paper primarily considers contact with unknown environments, problems related to gross motion control and impact control are neglected.

In order to underline the importance of connectionist learning approach, factors affecting task performance and stability in compliance control algorithms are analyzed. Dynamics model of the robot interacting with the environment is described by vector differential equation in the form:

$$H(q)\ddot{q} + h(q,\dot{q}) + J^T(q)F = \tau \tag{1}$$

where, $q = q(t)$ is an n-dimensional vector of robot generalized coordinates; $H(q)$ is an n x n positive definite matrix of inertia moments of the manipulation mechanism; $h = h(q,\dot{q})$ is an n-dimensional nonlinear function of centrifugal, Coriolis and gravitational moments; $\tau = \tau(t)$ is an n-dimensional vector of input control; $J^T(q)$ is an $n \times m$ Jacobian matrix connecting the velocities of robot end-effector and the velocities of robot generalized coordinates; $F = F(t)$ is an m-dimensional vector of generalized forces or of generalized forces and moments from the environment acting on the end-effector. The mathematical model of the environment in the frame of robot coordinates can be described by nonlinear differential equations:

$$M(q)\ddot{q} + L(q,\dot{q}) = -S^T(q)F \tag{2}$$

where $M(q)$ is an nonsingular n x n matrix; $L(q,\dot{q})$ is a nonlinear n dimensional vector function; $S^T(q)$ is an n x n matrix with rank equal to n, i.e. rank ($S$) = $n$. The one general environment model in common use can be specified by the following relation:

$$F = M^{'}\Delta\ddot{x} + \Sigma B_i^{'}\Delta\dot{x}^{\alpha_i} + \Sigma K_j^{'}\Delta x^{\beta_J} \tag{3}$$

where

$$\Delta x = x - x_0 \tag{4}$$

where $K'_j, B'_j$ are environment stiffness and a damping respectively, while $\alpha_i, \beta_j$ are integer exponents; $M'$ is a positive definite inertia matrix; $x_0$ denotes the coordinate vector in Cartesian coordinates of the point of impact between the end - effector (tool) and a constraint surface.

In the case of contact with the environment, the robot control task can be described as the robot motion along a programmed trajectory $q_P(t)$ representing a twice continuously-differentiable function, when a desired force of interaction $F_P(t)$ acts between the robot and the environment. Thus, the programmed motion $q_P$(t) and desired interaction force $F_P(t)$ cannot be arbitrary. Two functions must satisfy the following relation:

$$F_P(t) \equiv \left(fq_P(t), \dot{q}_P(t), \ddot{q}_P(t)\right) \tag{5}$$

A typical example is the considered control algorithm based on stabilization of the interaction force with a preset quality of transient processes; it has the following form [16]:

$$\begin{aligned}\tau &= H(q)M^{-1}(q)\left[-L(q,\dot{q}) + S^T(q)F\right] + \\ &h(q,\dot{q}) + J^T(q)\{F_P - \int_{t_0}^{t}\left[KFP\mu(\omega) + KFI\int_{t_0}^{t}\mu(\omega)dt\right]d\omega\}\end{aligned} \tag{6}$$

where $\mu(t) = F(t) - F_P(t)$; $KFP$ - is the $n \times n$ matrix of proportional force feedback gains; $KFI$ - is the n x n matrix of integral force feedback gains.

In this case, robot dynamics model (matrix $H(q)$, vector $h(q,\dot{q})$) has explicit influence on the performance of contact control algorithm, also having influence on PI force local gains. Also, it is clear that without knowing a sufficiently accurate environment al model (matrices $M(q), S(q), L(q)$) it is not possible to determine the nominal contact force $F_P(t)$. Furthermore, insufficiently accurately modeled robot and environment dynamics can significantly influence the contact task performances. Hence, the role of the neural networks is learning of matrices of robot dynamic models and unmodeled effects, as well as classification of environment parameters (members of environment al model matrices) and structure of environment models.

## The comprehensive connectionist learning and classification for compliance robotic tasks

The first objective in application of the learning compliance control algorithm is the learning of robot dynamic model and compensation of robot model uncertainties. For this purpose, the multilayer perceptron is used as a part of non-learning control strategies previously mentioned. Hence, matrix $H(q)$ and vector $h(q,\dot{q})$ should be exactly known in equation (1). These values may not be precisely available due to various structured-unstructured uncertainties of the dynamic model and/or the external disturbances. The aim of connectionist structure has a broader sense, because its aim is to compensate possible uncertainties and differences between the real robot dynamics and the assumed dynamics defined by the user in the process of control synthesis. In order to achieve good tracking performance with the presence of model uncertainties, multilayer perceptron is integrated into non-learning control law with the desired quality of transient process for interaction force:

$$P^{NN} = F_1(w_{jk}^{NNab}, q_P, \dot{q}_P, \ddot{q}_P, q, \dot{q}) \tag{7}$$

$$\tau = \hat{H}(q)\hat{M}^{-1}(q)\left[-\hat{L}(q,\dot{q}) + \hat{S}^T(q)F\right] + \hat{h}(q,\dot{q}) + J^T(q)\left\{F_P - \int_{t_0}^{t}\left[KFP\mu(\omega) + KFI\int_{t_0}^{t}\mu(\omega)dt\right]d\omega\right\} + P^{NN} \tag{8}$$

where $F_1$ is a nonlinear mapping for the perceptron NN; $P^{NN}$ is a compensation part of the learning control law; $w_{jk}$ are weighting factors for perceptron NN; $\widetilde{M}(q), \hat{L}(q), \hat{S}(q)$ are assumed functions of robot environment model. The inputs in the network are real values of internal robot positions and velocities beside the programmed values of internal positions, velocities and accelerations.

In order to enhance connectionist learning of general robot-environment model, new comprehensive method based on wavelet network classification of robot dynamic environment is proposed. A wavelet network can be described as an expanded perceptron with the so-called wavelet nodes as preprocessing units for feature extraction [17]. Its objective is to classify the characteristics of environments (parameters of environment al model matrices and environment al model structure) in an on-line manner. This classification capability is realized through two phases: off-line training process and on-line generalized classification. The wavelet nodes, which are adjusted during the learning phase, are a modified version $f(t-\tau_K / a_K)$ of a basic wavelet $f(t)$. The nodes are described by a time shift parameter $\tau_K$ and a scale parameter $a_K$, which is inversely related to the node's frequency ($\tau_K$ and $a_K$ are the parameters of the wavelet transformation). The input of the wavelet network, i.e. output of the wavelet node $\phi_{iK}$ represents the inner product of the node $f_K$ and the signal from robotic forcsensor $F_i$ (the index $i$ denotes the signal samples):

$$\phi_{iK} = \rangle f_K ; F_i \langle = \int_t f*\left(\frac{t-\tau_K}{a_K}\right)F_i(t)dt \tag{9}$$

The upper part of the wavelet network is represented by the topology of multilayer perceptron, which bases its classification decision on the wavelet node's output. For this implementation of wavelet network, various basic wavelet families can be used for e.g. Mexican hat wavelet, Meyer wavelet and Morlet wavelet.

**Table 1.** Input and output data for the classifier

| Input data for the classifier | Output data for the classifier |
|---|---|
| Transformed force signal | Silicon & $\langle 1 \rangle$ 0.0 |
| Transformed force signal | Rubber & $\langle 1 \rangle$ 0.05 |
| Transformed force signal | Plastic & $\langle 1 \rangle$ 0.1 |
| Transformed force signal | Steel & $\langle 1 \rangle$ 0.15 |

**Table 2.** Various environment models

| Models of robot environment |
|---|
| 1. $F = M'\Delta\ddot{x} + B'\Delta\dot{x} + K'\Delta x$ |
| 2. $F = M'\Delta\ddot{x} + B'\Delta\dot{x} + K'\Delta x + K_1\Delta x^3$ |
| 3. $F = M'\Delta\ddot{x} + B'\Delta\dot{x} + K'\Delta x + B_1'\Delta\dot{x}^3$ |
| 4. $F = M'\Delta\ddot{x} + B'\Delta\dot{x} + K'\Delta x + K_1\Delta x^3 + K_2\Delta x^2$ |
| 5. $F = M'\Delta\ddot{x} + B'\Delta\dot{x} + K'\Delta x + B_1\Delta\dot{x}^3 + B_2\Delta\dot{x}^2$ |

In the first phase of training, through realisation of the proposed compliance control algorithms, some data from robot force sensor $F(t)$ are observed and stored in specific data files. The acquisition process must be accomplished using various robot environments, starting with the environment with a low level of system characteristic and ending with the environment with a high level of system characteristic. Hence, using this approach, it is possible, in a similiar way, to include extension into the classification process, which is connected for recognition of environment al types with different structure of environment al models. After the acquisition process, during the extensive off-line training process, neural network receives a set of input-output patterns, where input variables in multilayer perceptron are wavelet transformation of force signals, while the desired output of network has a value between zero and unity which exactly defines the type of training robot environment. In the given example, training of neural network is accomplished with 4 different working environment (silicon, rubber, plastic, steel in Table 1.) and 5 different environment al models. (various forms of impedance models with additional damping and stiffness members in Table 2.). In this paper, learning algorithms for adjusting the network weights and parameters of wavelet transformation based on application of recursive least square (RLS) method [4] are considered.

It is generally assumed that training examples represent specific and commonly used environmental profiles. Hence, the success of the classification is determined by the "richness" of the training examples. Based on the non-learning versions of stabilizing control laws and neural network approach for learning of system uncertainties and classification of unknown robot environment previously described, it is possible to determine the whole structure of these control algorithms including the neural compensator and neural classifier. On the Fig.1, $y$ is the output of neural classifier. In the second phase of the comprehensive learning algorithm, the neural compensator and wavelet neural classifier work together in a synchronous way. Based on excellent generalization capabilities, neural classifier with fixed weighting factors is included into the learning algorithm (8) for determining optimal control parameters. The classifier produces a value between 0 and 1 at the output of the network, depending on the input real force data. Based on this value, through the process of

$$\tau = -H(q)\hat{M}'^{-1}(q)\left[\hat{B}'(q)+\hat{K}'(q)\right]+h(q,\dot{q})+ \left(J^T(q)-H(q)\hat{M}'^{-1}(q)\right)\left\{F_p-\int_{t_0}^{t}[KFP\mu(\omega)+ KFI\int_{t_0}^{t}\mu(\omega)dt]d\omega\right\} \quad (10)$$

linear interpolation, efficient determination of environmental parameters $M', B', K'$ or $M(q)$, $L(q,\dot{q}), S(q)$ with determination of environmental model structure is realized. This interpolation process is driven by stored parameters of dynamic models of different chosen environments and different chosen environmental model structure. In the given case, parameters of the dynamic models of different chosen environments are stored as information necessary for calculating the basic control algorithm. In the case of an unknown environment, information from neural classifier output can be efficiently utilized for calculation of environmental parameters by linear interpolation procedures.

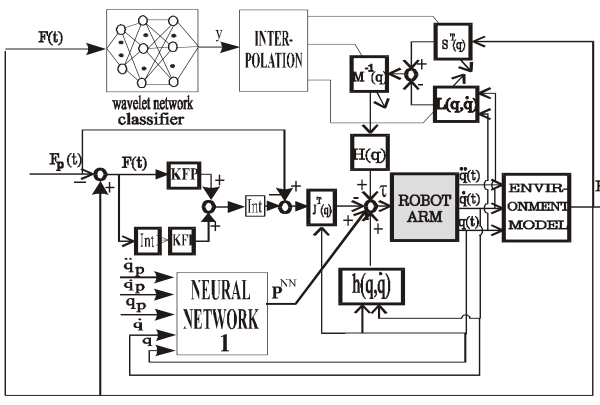


**Figure 1.** Scheme of connectionist control law

## Simulation studies

For demonstrating the performance of contact control schemes with neural networks, compliance control implementations are simulated using the robot PUMA560 for the circular writing taks on various robot environments. The end effector of robot exerts the force which is perpendicular to $y$-$z$ plane, performing circular path with diameter $d = 12$ cm.

For the application of stabilizing force interaction control algorithm in on-line training, the performance criterion based on selection of the same force PI gains is chosen. These PI force gains are synthesized using the same system frequencies for all different working environments and all different environmental profiles.

The influence of various working environments during acquisition process is shown in Fig.2. After the acquisition process, off-line neural network training is performed. The following network topology is chosen: 7 (number of wavelons in wavelet node) - 42 -24 -1. The uncertainties of the robot dynamics model and dynamic environment model are defined by parametric disturbances and additional white noise.

In the generalization test, the "off-line learned" wavelet neural classifier with fixed weighting factors is included in the control algorithm for the recognition of unknown robot environment. The second neural network for uncertainty compensation uses the same learning rules and parameters but different network topology (31-69-37-6). The profile model of environment using general impedance model with additional stiffness members is adopted. In this case, the robot environment with dominant stiffness $K$ = 65000 N/m is selected. The wavelet neural classifier based on input force data generates appropriate value at the output of the network. IN comparison, an example of application of impedance learning control laws with and without exact information of environmental stiffness after first learning epoch is given in Figures 3 and 4. It is evident that in case when there are no exact information about robot environment, the quality of position tracking performance is poor. Hence, inclusion of a neural classifier is very significant, because of the explicit inclusion of environment parameters in the control law.

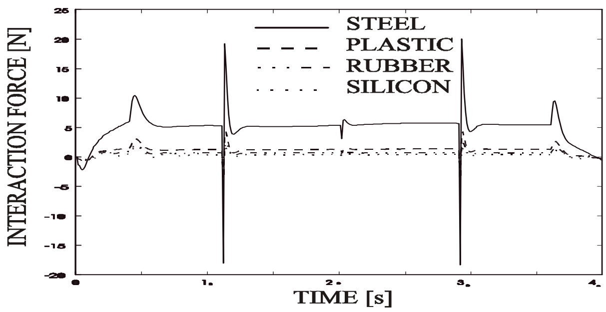


**Figure 2.** Interaction force–various environments

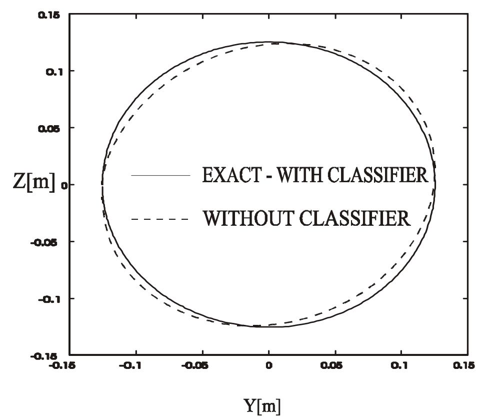


**Figure 3**. Comparison with and without the classifier

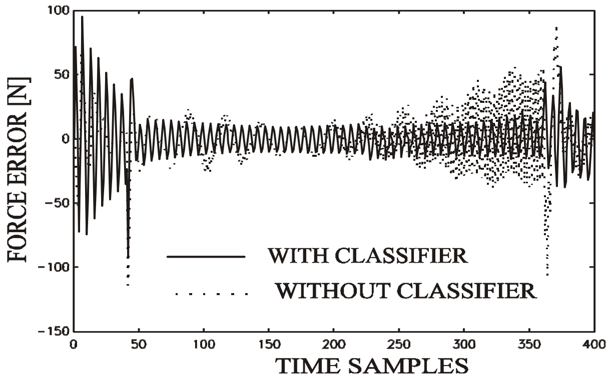


**Figure 4.** Force error with and without the classifier

## Conclusions

In this paper, a new control method for robotic compliance tasks based on wavelet connectionist classification and learning of unknown dynamic environment and robot system uncertainties is presented. Simulation experiments show that well-trained wavelet neural classifier along with on-line neural compensator in on-line control mode can significantly improve the performance of robot contact tasks in the uncertain environment.

## References

[1] VUKOBRATOVIC,M., KATIC,D.: *Robot Control Structures for High-Quality Learning in FlexibleManufacturing Tasks*, in Logistic and Learning for Quality Management and Manufacturing, (ed.B.Soucek), John Wiley & Sons, New York, 1994.

[2] ASADA,H.: *Teaching and Learning of Compliance using Neural Nets*: *Representation and Generalization of Nonlinear Compliance*, Proceedings of the IEEE International Conference on Robotics and Automation, Cincinnati, May 1990, pp.1237-1244.

[3] ASADA,H., LIU,S.: *Transfer of Human Skills to Neural Net Robot Controllers*, Proceedings of the IEEE International Conference on Robotics and Automation, Sacramento, April 1991, pp.2442-2448.

[4] GULLAPALI,V., GRUPEN,R., BARTO,A.: *Learning Reactive Admittance Control*, Proceedings of the IEEE International Conference on Robotics and Automation, Nice, May 1992, pp.1475-1481.

[5] GULLAPALI,V., BARTO,A., GRUPEN,R.: *Learning Admittance Mappings for Force-guided Assembly*, Proceedings of the IEEE International Conference on Robotics and Automation, San Diego, May 1994, pp.2633-2638.

[6] JEON,D., TOMIZUKA,M.: *Learning Hybrid Force and Position Control of Robot Manipulators*, Proceedings of the IEEE International Conference on Robotics and Automation, Nice, pp.1455-1460, May 1992.

[7] ARIMOTO,S., NANIWA,T.: *Learning Control for Robot Tasks under Geometric Endpoint Constraints*, Proceedings of the IEEE International Conference on Robotics and Automation", Nice, pp.1914-1919, May 1992.

[8] FUKUDA,T., SHIBATA,T., TOKITA,M., MITSUOKA,T.: *Adaptation and Learning by Neural Network for Robotic Manipulator*, Proceedings of the IMACS International Symposium on Mathematical and Intelligent Models in System Simulation, Brussels, September 1990.

[9] JUNG,S., HSIA,T.C.: *On Neural Network Application to Robust Impedance Control of Robot Manipulators*, Proceedings of the IEEE International Conference on Robotics and Automation, Nagoya , pp.869-874, May 1995.

[10] ŠEŠLIJA,D., VUKOBRATOVIĆ,M.: *Environment Parameters Identification for the Control of Robotized Machinig*, Proceedings of the first ECPD International Conference on Advanced Robotics and Intelligent Automation, Athens , pp.632-637, Septemer 1995.

[11] VENKATARAMAN,S.T., GULLATI,S., BARHEN,J., TOOMARIAN,N.: *A neural network based identification of environment models for compliant control of space robots*, IEEE Transactions on Robotics and Automation, October 1993, Vol.9, pp.685-697.

[12] CHA,H., CHO,H.S., KIM,K.S.: *Design of a force reflection controller for telerobot systems using neural network and fuzzy logic*, paper submitted for publication in Journal of Intelligent and Robotic Systems,1995.

[13] TAROKH,M., BAILEY,S.: *Force tracking with unknown environment parameters using adaptive fuzzy controllers*,' in Proceedings of the IEEE Iternational Conference on Robotics and Automation, Minneapolis, pp.270-275, April 1996.

[14] KATIC,D., VUKOBRATOVIC,M.: *Highly efficient robot dynamics learning by decomposed connectionist feedforward control structure*, IEEE Transactions on Systems,Man and Cybernetics, 1995, Vol.25, No.1, pp.145-158.

[15] KATIC,D., VUKOBRATOVIC,M.: *Robot Compliance Control Algorithm Based on Neural Network Classification and Learning of Robot-Environment Dynamic Mocels*, Proceedings of 1997 IEEE International Conference on Robotics and Automation, Albuquerque, April 1997.

[16] VUKOBRATOVIC,M., EKALO,Y.: *New approach to the control of manipulation robots interacting with dynamic environment*, Robotica, 1996, Vol.14, pp.31-39.

[17] SZU,H.H., TELFER,B., KADAMBE,S.: *Neural Network Adaptive Wavelets for Signal Representation and Classification*, Optical Engineering, September 1992, Vol.31, No.9, pp.1907-1916.

Received: 15.01.2006.

# Neuronski upravljački algoritam za robotske kontaktne zadatke zasnovan na “wavelet” mrežnom klasifikatoru

**U ovom radu, predložena je nova sveopšta inteligentna upravljaćka strategija zasnovana na neuronskom učenju neodređenosti robotskog sistema I “wavelet” mrežnoj klasifikaciji nepoznate robotske radne okoline. Predložena “wavelet” neuronska mreža klasifikuje karakteristike radne okoline, određuje upravljačke parametere za upravljanje robotom u kontaktnim zadacima i u koordinaciji sa osnovnim kontaktnim upravljačkim algoritmom, redukuje uticaj neodređenosti dinamičkog modela robota. U cilju verifikacije predloženog pristupa, simulatcioni eksperimenti sa robotom u kontaktu sa dinamičkom okolinom su realizovani. Simulacija na računaru pokazuje da je greška sile znatno manja kada sistem radi sa NN klasifikatorom nego bez njega.**

*Ključne reči*: **robotika, roboti, upravljački algoritam, neuralna mreža, simulacioni model, inteligentno upravljanje.**

# Нейронный управляющий алгорифм для робототехнических контактных задач, базированный на Ыавелет-сетевом классификаторе

В настоящей работе предложена новая всеобъемлющая интеллектуальная управляющая стратегия, базированная на нейронном учении неопределённости робототехнической системы и на Ыавелет-сетевой классификации неизвестной робототехнической рабочей среды. Предложенная Ыавелет -нейронная сеть классифицирует характеристики рабочей среды, определяет управляющие параметры для управления роботом в контактных задачах и в координации с базовым контактным управляющим алгорифмом, редуцирует влияние неопределённости динамической модели робота. С целью верификации предложенного подхода, реализованы имитационные эксперименты с роботом в контакте со динамической окружающей средой.

*Ключевые слова*: робототехника, роботы, управляющий алгорифм, нейронная сеть, имитационная модель, интеллектуальное управление.

# Algorithme de commande à neurones pour les contactes tâches robotiques basé sur le réseau classificateur Wavelet

**On propose dans ce travail une nouvelle stratégie compréhensive et intelligente de commande basée sur le savoir de neurones de l'incertitude du système robotique et sur la classification du réseau WAVALET de l'ambiance de travail inconnu de robot.Le réseau neurone WAVALET proposée classifie les caractéristiques de l'ambiance de travail, détermine les paramètres de commande pour diriger le robot dans les tâches de contact ainsi que dans la coordinnation avec l'algorithme basique contact de commande, réduit l'influence de l'incertitude du modèle dynamique de robot.Pour vérifier l'approche proposée on a réalisé les essais de simulation avec le robot en contact avec l'ambiance dynamique.**

*Mots clés*: **robotique, robots, algorithme de commande, réseau de neurones, modèle de simulation, commande intelligente.**