

Lejla Banjanovic-Mehmedovic, Fahrudin Mehmedovic, Ivan Bosankic, Senad Karic

# Genetic Re-planning Strategy of Wormhole Model using Neural Learned Vibration Behavior in Robotic Assembly

DOI 10.7305/automatika.54-4.309  
UDK 007.52; 519.713  
IFAC 2.8.4; 2.6; 1.1.0

Original scientific paper

This paper investigates the genetic based re-planning search strategy, using neural learned vibration behavior for achieving tolerance compensation of uncertainties in robotic assembly. The vibration behavior was created from complex robot assembly of cogged tube over multistage planetary speed. Complex extensive experimental investigations were conducted for the purpose of finding the optimum vibration solution for each planetary stage reducer in order to complete the assembly process in defined real-time. However, tuning those parameters through experimental discovering for improved performance is a time consuming process. Neural network based learning was used to generate wider scope of parameters in order to improve the robot behavior during each state of the assembly process. As a novel modelling formalism of reactive hybrid automata, we propose the Wormhole Model with both learning and re-planning capacities (WOMOLERE). For our application, the states of hybrid automaton include amplitudes and frequencies of robot vibration module. The transition action is a function of minimal distance and uncertainty effects due to jamming during the assembly process. The results suggest that the methodology is adequate and could be recognized as an idea for designing of robot surgery assistance methods, especially in soft-robotics.

**Key words:** Hybrid Automaton, Learning Behavior, Re-planning Search Strategy, Robot Assembly, Wormhole Model

**Genetski bazirana strategija re-planiranja modela crvotočine korištenjem neuronski naučenog vibracijskog ponašanja u robotskoj montaži.** Ovaj članak prezentira strategiju re-planiranja kretanja, baziranu na genetskom algoritmu, korištenjem neuronski naučenog vibracijskog ponašanja u cilju postizanja kompenzacije tolerancije neizvjesnosti u procesu robotske montaže. Vibracijsko ponašanje je kreirano iz kompleksne robotske montaže nazubljene cjevčice preko višestupanjskog planetarnog reduktora brzine motora. Provedeni su brojni eksperimenti s ciljem određivanja optimalnih amplituda i frekvencija vibracijskog modula robota za svaki stupanj reduktora s ciljem završetka procesa montaže u definiranom realnom vremenu. Međutim, podešavanje ovih parametara kroz eksperimente u cilju unaprjeđenja performansi je vremenski zahtjevan proces. Učenje bazirano na neuronskim mrežama je korišteno za generiranje šireg opsega parametara stanja modela u cilju unaprjeđenja robotskog ponašanja tijekom svake faze procesa montiranja. Kao novi formalizam modeliranja reaktivnog hibridnog automata, predložili smo model crvotočine, sa sposobnostima i učenja i re-planiranja (WOMOLERE). Za našu aplikaciju, stanja hibridnog automata sadrže amplitude i frekvencije robotskog vibracijskog modula. Akcija tranzicije je funkcija minimalne distance i učinaka neizvjesnosti uslijed zaglavljenja pri procesu montiranja. Rezultati pokazuju da je metodologija prikladna i kao ideja se može koristiti u dizajniranju metoda robotske asistencije pri operacijama, osobito u soft robotici.

**Ključne riječi:** hibridni automat, učenje ponašanja, strategija re-planiranja, robotska montaža, model crvotočine

## 1 INTRODUCTION

Planning is the key ability of intelligent systems, as it increases their autonomy, reliability, efficiency and flexibility, through the construction of action sequences and achieving their goals. In artificial intelligence, planning originally is a search for a sequence of logical operators or actions that transforms an initial world state into a de-

sired goal state [1]. Robot motion planning usually ignores dynamics and considers other aspects, such as uncertainties, differential constraints, modeling uncertainties and optimality. The robotic assembly, wheelchair navigation, sewer inspection robot, autonomous driving system in urban and off-road environments, task planning of machine for the robotic systems are all examples of au-

onomous systems, which solve path planning/re-planning problems. Dynamic re-planning is necessary because at any time during the execution of its tasks, the robot might unexpectedly run into problems [2]. The typical approach used for re-planning is repair plans, which are prepared in advance and invoked to deal with specific exceptions during the execution. This type of approach may work well in a relatively static and predictable environment. In a more dynamic and uncertain environment, where it is hard to anticipate possible exceptions, the re-planning generates a (partially) new plan in case when one or more actions have problems during execution [3].

The mechanical assembly is the dominant application domain of industrial robots. A key problem in high-precision robotic assembly tasks, is how to make robots operate reliably in the presence of uncertainties (such as mechanical, control, sensor, kinematical or dynamical uncertainties). The main difficulty in automated assembly is the kinematical uncertainty in the relative position of the parts that are being assembled [4]. Since there is no general and unconditional solution for the problem, the uncertainty handling for robot assembly must be a dynamic process involving sensory information and general knowledge of contacts among the assembled parts. The success is guaranteed only if certain constraints on the nominal design parameters, tolerances, and sensor error parameters are enforced. For robotic assembly, the tolerance is especially a difficult problem because in the process of assembling it must be compensated but it takes time and requires corresponding algorithms.

Compliant motion control (or force control, or torque control) is a reactive control model in which a tight control loop is expected to make comparatively simple decisions based on the measured signal outputs of a variety of sensors measuring velocity, position, acceleration, and force. The application of force control is essentially one of relating measured forces to one or more system variables in the form of a mass-spring damper for tuning and stability. There exists a wide variety of compliant motion control algorithms relating measured force to virtually any combination of position, velocity, acceleration, and applied force [5,6]. The industrial world has been slow to adopt force-based practices in automating assembly tasks [7]. There are several factors that have influenced this slow migration, not least of which is the cost involved, both in terms of the time necessary to implement and the steep learning curve. Some of the most prohibitive aspects are the failed promises of reliability and throughput; reliable solutions are not fast, and fast solutions are not reliable.

One of novel methods [8] demonstrates precise motion control using parallel robots with manufacturing tolerances and inaccuracies by migrating the measurements from their joint space to task space in order to decrease the control

system's sensitivity to any kinematical uncertainty rather than calibrating the parallel plant. The problem of dynamical model uncertainties and its effect on the derivation of the control law is also addressed in this work through disturbance estimation and compensation. The both task space measurement and disturbance estimation were combined to formulate a control framework that is insensitive to either kinematical and dynamical system uncertainties.

A concept that allows the cognitive automation of robotic assembly processes is presented in [9]. To verify the concept, an assembly cell comprised of two robots was designed. For the purpose of validation a customer-defined part group consisting of Hubelino bricks is assembled. One of the key aspects for this process is the verification of the assembly group. The software component was designed to perceive depth and color data in the assembly area. This information is used to determine the current state of the assembly group and compared to a CAD model for validation purposes. The implications for an industrial application were demonstrated by transferring the developed concepts to an assembly scenario for switch-cabinet systems.

To address the shortcomings of the motion primitive approach, adaptive techniques in the form of event-based search strategies recognize and attempt to compensate for part and position variance. In many cases a given assembly task may have numerous strategies defined for its completion. For instance, a peg-in-hole assembly may be completed by "dumb" searches in which the peg to be inserted is moved around a candidate hole position (either randomly, or by a structured geometric pattern like rasters [10] or spirals) until it can be pushed in. Alternatively, more explicit methods can be employed that intelligently probe the candidate hole position and, based on the effector position and force moments, accurately identify the location and orientation of the hole into which the peg will be inserted [11]. Other assemblies that are more specific in nature (for example, automobile clutch assemblies) can be parameterized and generalized, or broken down into separate motion primitives.

The complex tasks such as multi-staged assemblies with component location uncertainties require an adaptive system which capable of automatically adjusting to both identify and compensate for changes in operational conditions. This capacity may either be explicitly programmed or automatically adapted to via machine learning. In either case, some form of feedback basis is required for the optimization process; this task-specific feedback (e.g., time or bandwidth) is considered for process optimization, and is distinct from the feedback for force-control parameter tuning. As important as the time required to complete an assembly, successfully completing assemblies rather than prematurely aborting them due to time constraints or improperly seated parts is an integral component of process

automation [12, 13].

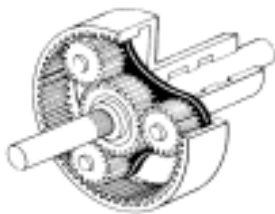
Some other intelligent-control methods have been researched [14, 15]. For example, work [15] describes an intelligent mechanical assembly system. A correct assembly path is chosen by using a form of Genetic algorithm search, so the new vectors are evolved from the most successful “parents”.

As a novel modelling formalism of reactive hybrid automata, we propose the biologically inspired Wormhole Model with both learning and re-planning capacities (WOMOLERE). This paper investigates the genetic based re-planning strategy, using neural learned behavior for achieving tolerance compensation in robotic assembly. For our application, the states of hybrid automaton include amplitudes and frequencies of robot vibration module. Transition action is a function of the minimal distance and uncertainty effects due to jamming during the assembly process.

The behavior model is created from complex robot assembling of multistage planetary speed reducer. Assembly of the tube over the planetary gears was recognized as the most difficult problem of overall assembly and favourable influence of vibration and rotation movement on compensation of tolerance was analyzed. The neural network based learning gave us extended successful vibration module solutions for each stage of reducer. With this extended vibration parameters as the main source of information for the Planning/Re-planning Task, we introduce intelligent search strategy, which overcomes uncertainties during the robot assembly process.

## 2 ROBOT ASSEMBLY BEHAVIOR SETTING

The main difficulty in the robot assembly of planetary speed reducers is the installation of the tube over planetary wheels. Namely, the teeth of all three planetary wheels must be assembled with the cogged tube (Fig. 1).



*Fig. 1. One of the stages at planetar reducer*

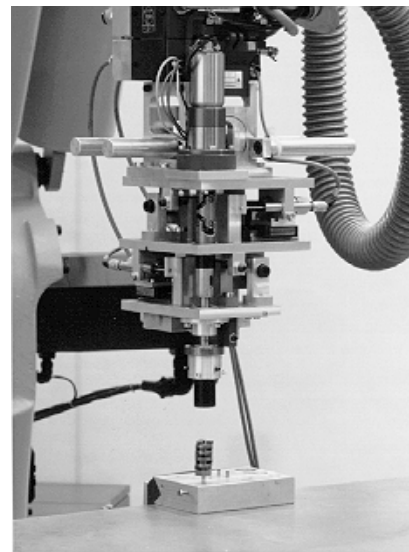
In this research, the complete assembly of each part of planetary reducer has not been considered, but only the process of connecting the cogged tube to the five-stage



*Fig. 2. Exterior view of planetary speed reducer*

planetary speed reducer (cross-section 20mm, height five degrees 36mm), Fig. 2.

By solving the problem of assembling the gears, there will be no problem to realize the complete assembly of planetary speed reducer. For the process of assembly, the vertical-articulated robot with six-degrees of freedom, type S-420i of the firm FANUC has been used, completed by vibration module, developed at Fraunhofer- Institute für Produktionstechnik and Automatisierung (IPA) in Stuttgart, Germany (Fig. 3).



*Fig. 3. Vibration module*

The analysis of the assembly process showed that movement based on vibration and rotation acted positively on the course of the process. The vibration module produced vibration in the x- and y- direction and rotation around the z-axis. By starting the robot work, the vibration module vibrated with determined amplitude (to  $\pm 2$ mm) and frequency (to max. 10Hz) for each stage of reducer. The ideal Lisague figures (double eight, circle and line) have been used as figures of vibration for extensive exper-

iments. The vibration figure horizontal EIGHT (Fig. 4) was selected for further experiments, because we achieved the best performance in the assembly process. In that case, the frequency ratio between the lower and upper plate is  $f_D/f_U = 2$ .

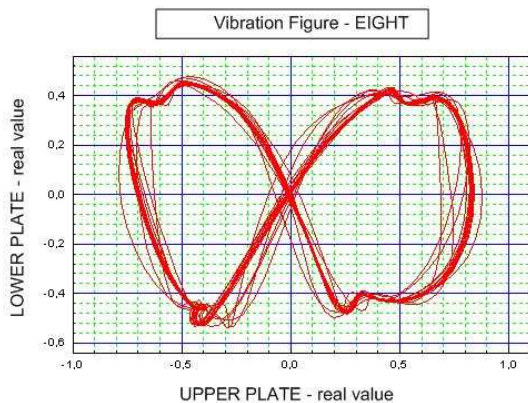


Fig. 4. One example of vibration figure –EIGHT

During the robot assembly of two or more parts we encountered the problem of tolerance compensation.

According to the functionality, the individual systems of tolerance compensation can be divided into:

1. The controllable (active) system for tolerance compensation, where on the base of the sensor information on tolerance, the correction of movement is made for the purpose of tolerance compensation
2. The uncontrollable (passive) system for tolerance compensation where the orientation of external parts is achieved by the means of an advanced determined strategy of searching or influenced by connection forces
3. Combination of the above two cases.

For this system of assembly, the passive mechanism of tolerance compensation has been used with a specially adjusted vibration of installation tools. In order to compensate the tolerance during robot assembly, in an experimental setup, we used the ‘search strategy’, which adjusted amplitudes and frequencies gained from the experimental experience (amplitudes of upper and lower plate, frequencies of upper and lower plate). The optimal amplitudes for all stages of the reducer were  $A_D = A_U = 0.8\text{mm}$ .

We noticed from experiments that smaller frequencies of vibration were better ( $f_D/f_U = 4/2$  or  $6/3$ ) for the first and second stage (counting of stages starts from up to down), while for each next stage the assembly process was improved with higher frequencies ( $f_D/f_U = 8/4$  or  $10/5$ ).

The assembly process started with the gripper positioned together with cogged tube exactly 5mm above the base part of the planetary reducer and then moving in the direction of the negative z-axis in order to begin assembling. In case of jamming because of different physical reasons (position, friction, force etc.), the robot will return to the previous stage, where the jamming has happened. The technique of “blind search” was used in an optimal parameter space with repeated trials at manipulation tasks. When the jamming is solved, the robot will keep moving until it reaches the final point in the assembly [16].

The time of the complete assembly process for a given range of speeds depends on the frequency, amplitude of upper and lower plate of vibration module, amplitude and frequency of motor rotation and the speed of motor movement in z-direction. The fastest process of the complete assembly process of 4s was the robot movement speed value of 16mm/s.

Complex extensive experimental investigations were conducted for the purpose of finding the optimum solution, because many parameters had to be specified in order to complete the assembly process in defined real-time. However, tuning those parameters through experimental discovering for improved performance is a time consuming process. To make this search strategy more intelligent, additional learning software was created to enable improvements of performance [17].

Our strategy in this paper is focused on modeling tasks of tolerance compensation using the Re-planner Learning Hybrid Automaton (WOMOLERE) in robot assembly.

### 3 WORMHOLE MODEL AS HYBRID AUTOMATON

Hybrid systems are dynamical systems that consist of discrete controls embedded in the continuous environments. Due to their large representation in the real-world, especially in the process and the automotive industries, the significance of hybrid systems cannot be overemphasized [18].

One of the most used model-based formalism of hybrid systems is the hybrid automaton. The expressiveness of this formalism enables the modeling of both discrete and continuous dynamics, with the inclusion of the timing and probabilistic information (i.e. modeling the times and the probabilities of signal changes). Model-based approaches are used in different applications, e.g. in optimization, anomaly detection, testing and design.

Although hybrid automata have huge significance in modeling hybrid systems, there is a serious lack in the hybrid automata learning. Despite the dominant use of hybrid automata in technical disciplines, the first attempts toward

their automatic learning came from biological application. The algorithm given in [19] is learning the dynamics of the action potentials, i.e. the electrical signals of certain types of cells in the living organisms. However, this algorithm does not account for discrete signals. The second example is learning of hybrid automaton for anomaly detection in production plants [20].

We propose here a novel biological inspired hybrid automaton model (WOMOLERE), which overcomes uncertainties with learned behavior solutions and re-planning capabilities in the application of rigid-link robot assembly.

The configuration space of each wormhole’s knuckle is discretized. Each knuckle of wormhole will be searched in order to make an optimal path from start to target position. In the following, the formal definitions of the components are given.

**Definition 1** The optimal basis cluster parameters are a set of optimal parameters, gained from experiments and can be presented for each knuckle of wormhole  $k=1, \dots, N$  in 2D space:

$$\xi_B^k = ((x_1^k, y_1^k), \dots, (x_m^k, y_m^k)), k = 1, \dots, N. \quad (1)$$

The optimal extended cluster parameters are a set of optimal extended parameters, gained through learning of system’s behavior and can be presented for each knuckle of wormhole  $k=1, \dots, N$  in 2D space:

$$\xi_E^k = ((x_1^k, y_1^k), \dots, (x_l^k, y_l^k)), k = 1, \dots, N. \quad (2)$$

**Definition 2** The re-planning strategy through wormhole of  $N$  depending knuckles using learned parameters can be presented with

$$S_{RP} = (\Psi_B, \Psi_E, \Phi_B, \Omega, T) \quad (3)$$

where each knuckle of wormhole  $k=1, \dots, N$  is described with:

1. basis cluster parameters  $\xi_B^k$

$$\Psi_B = (\xi_B^1, \xi_B^2, \dots, \xi_B^k), k = 1, \dots, N. \quad (4)$$

2. extended cluster parameters  $\xi_E^k$

$$\Psi_E = (\xi_E^1, \xi_E^2, \dots, \xi_E^k), k = 1, \dots, N. \quad (5)$$

3. uncertainty for each knuckle of system during planning/re-planning process

$$\omega_k, \Omega = (\omega_1, \dots, \omega_k), k = 1, \dots, N. \quad (6)$$

4. learning behavior transform function  $\Phi_B$  and

5. transition actions  $a_k^{k+1}$  between knuckles of wormhole,

$$T = (S_k^*, S_{k+1}^*, a_k^{k+1}), k = 1, \dots, N. \quad (7)$$

where  $T$  gives the set of transitions.

**Definition 3** The learning behavior function  $\Phi_B$

$$\Phi_B : \Psi_B \rightarrow \Psi_E \quad (8)$$

transforms the set of basis clusters parameters  $\Psi_B = (\xi_B^1, \dots, \xi_B^k, \dots, \xi_B^N), k = 1, \dots, N$  in set of extended clusters parameters  $\Psi_E = (\xi_E^1, \dots, \xi_E^k, \dots, \xi_E^N), k = 1, \dots, N$ , i.e.:

$$\Psi_E = F_B(\Psi_B, \Omega) \quad (9)$$

where

$$\xi_E^1 = f_B^1(\xi_B^1), \dots, \xi_E^k = f_B^k(\xi_B^k), \dots, \xi_E^N = f_B^N(\xi_B^N) \quad (10)$$

are universal approximator functions, used as learning functions.

**Definition 4** The fitness transition function  $L_M$  between all knuckles of wormhole is defined with

$$L_M = \min(\sum_{k=1}^N d_k^{k+1}(S_k^*, S_{k+1}^*, a_k^{k+1}) + K \sum_{k=1}^N w_k) \quad (11)$$

where  $d_k^{k+1}$  is minimum distance from selected optimal value  $S_k^* = (x_i^k, y_i^k), i = 1, \dots, l$  of current knuckle to selected optimal value of next wormhole’s knuckle  $S_{k+1}^* = (x_i^{k+1}, y_i^{k+1}), i = 1, \dots, l$  using transition action  $a_k^{k+1}$ ; value  $w_k$  indicates uncertainty effects for each knuckle.

Genetic algorithm calculates minimal fitness transition function  $L_M$  which depends on how suitable is the solution (path) according to physics boundary problem.

#### 4 RE-PLANNER STRATEGY OF WORMHOLE MODEL

The problem of finding a sequence of actions to reach a desired goal state is task planning. This is a classical AI problem that is commonly formalized using a suitable language to represent task relevant actions, states and constraints [21]. The robot has to be able to plan the demonstrated task before executing it if the state of the environment has changed after the demonstration took place. The objects to be manipulated are not necessarily at the same positions as during the demonstration and thus the robot may be facing a particular starting configuration it has never seen before.

The planning under uncertainty is a hard job and requires re-planning task structure. The re-planning is used as a specific case of planning process.

We propose the Re-planning Strategy of Wormhole Model using Learning Behavior. Our planning/re-planning search strategy consists of three important phases:

1. *Learning phase* (from basic experiments, trying various actions and data collecting).
2. *Planning phase* (off-line modus).
3. *Re-planning phase* (on-line modus).

We can describe each phase of this re-planning strategy as follows:

**Learning phase.** Using learning behavior transform function  $\Phi_B$ , we create a set of optimal extended parameters  $\Psi_E$  as a source information for the Planning/Re-planning Task.

**Planning phase.** The initial planning problem could be presented as a plan

$$P_a = (S_0, S_N, a, L_M) \tag{12}$$

where  $S_0$  is an initial state parameter,  $S_N$  is a goal state parameter and a plan  $P_a$  is a network of actions  $a_k^{k+1}$  that lead from  $S_0$  to  $S_N$  (result from optimal search strategy).

**Re-planning phase.** If an action  $a$  in  $P_a$  fails, we define a re-planning area  $R_A = \{a'\}$ .  $R_A$  is treated as a partially/new plan and a re-planning problem is constructed

$$P'_{a'} = (S'_k, S_N, a', L'_M) \tag{13}$$

We take enough offset  $\varepsilon$  from critical optimal point  $S_k$  to another optimal solution  $S'_k$  which is the new start point used by  $R_A$

$$S'_k = f(S_k, \varepsilon). \tag{14}$$

The strategy continues searching from a new selected optimal value of current knuckle to selected optimal value of next wormhole's knuckle using the new plan  $P'_{a'}$  with transition action  $a'$ , which is a function of new minimum distance and uncertainty effects. If new action in  $P'_{a'}$  fails, we will define  $P''_{a''} = (S''_k, S_N, a'', L''_M)$  and so on in order to achieve the goal point.

When calculating the total fitness function for new plan, the cost of returning to previous phase was excluded, so the fitness function consists of two parts: a fitness function before re-planning (from start point to last feasible point) and a fitness function of the new re-planned path (from new start point to goal point). In this way, the fitness function values can be compared with the values where re-planning does not occur.

Figure 5 presents the Re-planning Search Strategy effects using learned behavior parameters (biologically inspired Wormhole Model).

Figure 6 presents the re-planning search strategy of Wormhole Model for the robot assembly. Using the WOM-ELERE hybrid automaton in robotic assembly is focused

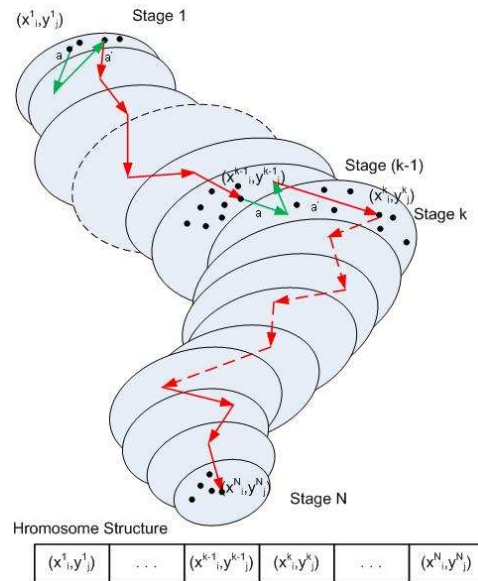


Fig. 5. Re-planning Search Strategy effects using learned behavior parameters

on modeling tasks of tolerance compensation, which transforms original problem in a problem of path planning/re-planning using learned behavior. The inputs into the planning process are geometric descriptions of the robot and the environment through the parameter space and the initial and final position of the robot ( $q_i, q_f$ ). The output of the path planning process is the path  $T(q_i, q_f)$  from initial  $q_i$  to target position  $q_f$ .

The worm knuckles include relevant state variables (amplitudes and frequencies of robot vibration module). The requirements for the process of path planning between the wormhole knuckles are: minimum length of the path between relevant state variables (in our research are associated with the minimum of time execution) and the choice of the parameters which comply the other constraints (physical limitation).

We suggest the neural network based learning because it gives us new successful vibration module solutions for each stage of the planetary reducer. Combing the efforts of the planner and learned optimal values, the re-planner is expected to guarantee that hybrid automaton (WOM-ELERE) enters the region of convergence of its final target location. The error model (on Fig. 6) is used to model various dynamic effects of uncertainties and physical constraints made by jamming.

## 5 NEURAL LEARNED VIBRATION BEHAVIOR OF ROBOT ASSEMBLY

In order for the robots to react to stochastic and dynamic environments, they need to learn how to optimally

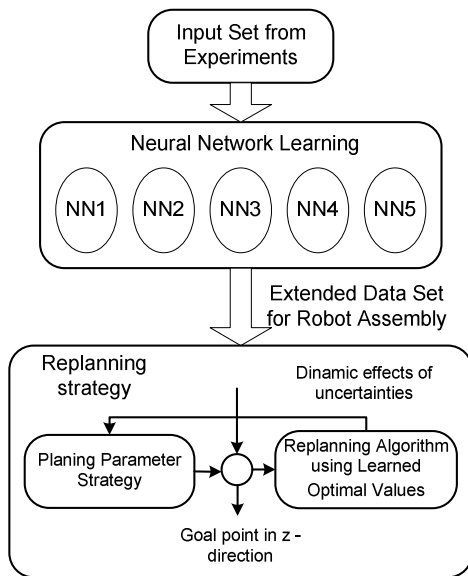


Fig. 6. Re-planning Search Strategy using Neural network Parameters Learning in Robot Assembly

adapt to uncertainty and unforeseen changes [22]. Artificial neural networks (ANN), as universal approximators, are capable of modelling complex mappings between the inputs and outputs of a system up to an arbitrary precision. Another advantage of neural networks is learning [23]. Learning is a process, through which the implicit rules are extracted from patterns of experience. These rules become the foundation for generalizations in the networks that enable a robot to respond [24].

The formalism from our strategy is accommodated to the learning task. Neural network based learning was used in this research to generate wider scope of parameters in order to improve the robot behavior. The amplitude and frequencies vibration data were collected during the assembly experiments and used as sources of information for the learning algorithm.

In our research we used the Multi-layer feed-forward network (MLF) neural network that contains 10 tansig neurons in a hidden layer and 1 purelin neuron in its output layer. The feed-forward neural networks were formed and tested for each stage of the assembly process. Each one was initialized with random amplitudes  $A_D = A_U = A_i$  between 0 and 2 and frequencies values  $f_i$  between 0 through 4. Namely, the range of the frequencies measurement is normalized by mapping from frequencies ratio  $f_D/f_U = (4/2, 6/3, 8/4, 10/5)$  onto the range of the state frequencies values (0 through 4). For training the MLF network, we used 35 vibrations sets for each 5 phases of assembly. The mean square errors (MSE) during the training of 5 MLF networks were achieved for 7-10 epochs. Two

thousand data points were taken as a testing sample.

The feed-forward neural networks were formed and tested for each stage of assembly process. Figure 7, Figure 8 and Figure 9 represent learning of new optimal stage vibration sets indicated by their respective picture.

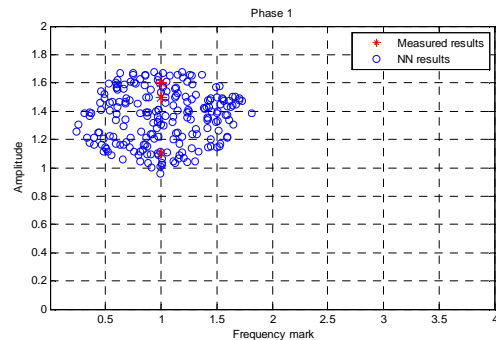


Fig. 7. Results of neural network training-stage one

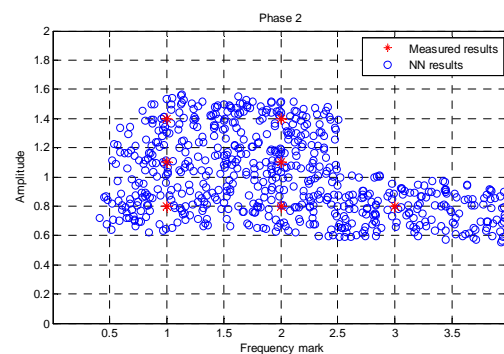


Fig. 8. Results of neural network training-stage two

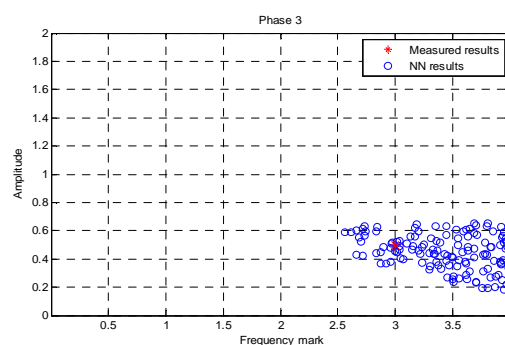


Fig. 9. Results of neural network training-stage three

The results show that the scope of adjusted vibration parameters obtained from autonomous learning has extended in respect to adjusted vibration sets from the experimental robot assembly. In this way, we discretized the

parameter space of the wormhole model. We can see that a critical moment in the assembly process is the second phase, which represents the medium clutter position of optimal vibration parameter sets through stages. With these extended vibration parameters as the source information for the planning/re-planning task, we introduce the genetic based search strategy through the wormhole model.

## 6 RESULTS OF ROBOTIC ASSEMBLY RE-PLANNER STRATEGY

Genetic algorithms are a class of adaptive methods that can be used to solve search and optimization problems involving large search spaces.

In this research, the genetic algorithm, a powerful non-traditional approach, has been acquired for search solving [25]. The chromosome structure must have sufficient information about the entire path from the start point to the endpoint in order to represent the complete state space in each stage. The encoding technique uses vibration parameters of the robot vibration module as a part of the chromosome (Fig. 10).

The population of paths is evaluated during each generation and it is based on the fitness of path, which depends on how suitable the solution (path) is according to the physics boundary problem. Genetic algorithm calculates the fitness function  $F$ , use (11) for  $N=5$ , where  $d_k^{k+1}$  is a distance from the selected optimal value  $S_k^* = (A_i^k, f_i^k), i = 1, \dots, l; k = 1, \dots, 5$  of a current stage to the selected optimal value of next stage  $S_{k+1}^* = (A_i^{k+1}, f_i^{k+1}), i = 1, \dots, l$  gained from learning process:

$$d_k^{k+1} = \sqrt{(A_i^{k+1} - A_i^k)^2 + (f_i^{k+1} - f_i^k)^2}. \quad (15)$$

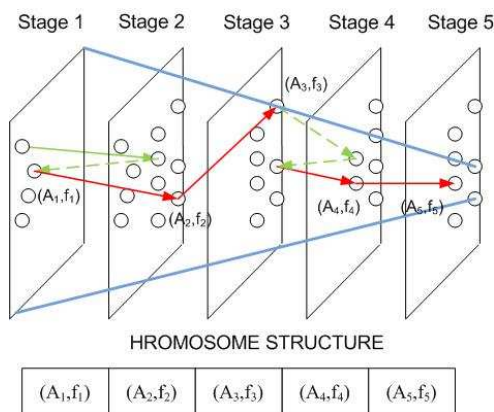


Fig. 10. Chromosome structure for all five stages

Weighting factor  $K$  must be set to be larger than the maximum possible sum of  $d_k^{k+1}$ , so the algorithm can eliminate

infeasible (jammed) solutions from the population. Therefore, value  $K = 5000$  is chosen to calculate the fitness function.

Genetic based agent has been implemented in C# (Microsoft Visual Studio.NET 2005). GA applies techniques such as crossover, selection, and mutation. Implementation in the algorithm included three ways of crossing over: node crossover, which combines bits of two parents in each phase (multi-point crossover where a number of points equals the number of phases) and path crossover, which copies the first part of the path from one parent, and the second part from the other (crossing over can occur only in specific points, on the border of two phases). An asexual crossover, swap crossover, was also added – it included swapping the amplitudes and frequencies in two adjacent phases of single chromosome.

Elitism refers to the process of ensuring that the best individuals of the current population survive to the next generation. Since there is a very large infeasible area, there is a possibility that the feasible solutions could be lost through generations, and the reducer would jam as a result. Therefore, elitism was introduced to help preserve quality solutions in the population.

It is possible in program way to adjust characteristic parameters of GA. For this experiment, the parameters used are: population number: 100, maximal number of generation: 500, probability of crossover operation: 60%, probability of mutation operation: 4%, percentage of elite: 5%.

If jamming occurs, it is necessary to generate a (partially) new plan, i.e. return to the previous phase and restart the algorithm to generate a new valid solution. Amplitude and frequency of the new start point should be modified. Since the algorithm is not restarted from the beginning (except when jamming occurs in the second phase), the chromosome length is modified – a new chromosome is shorter since it contains smaller number of phases. In order to decrease the possibility of successive jamming, a small offset is added to the last valid point. This offset is generated randomly

$$O = K \times \exp(-x^2) \quad (16)$$

using Gaussian distribution, where  $K=50$  for this particular search space ([0, 512] for each parameter in chromosome). Number  $x$  is chosen randomly. Offset is applied for both amplitude and frequency.

The performance of Re-planning Motion Agent is demonstrated in Table 1 and Table 2, where the actual values of frequencies are  $f_b = 2 \times f_a$ .

We use the random start point in feasible vibration parameter space: (0.70, 2.9) for first experiment (Table 1). In case of detecting the error event signal at the fourth level, the search strategy tries instead of the optimal value (1.53,



Table 1. The parameter settings and value of the fitness function for first experiment with Re-planning Agent

States	Amplitude and frequencies values for states	
	Planned path $(A_k, f_{ak})$	Re-planned path $(A'_k, f'_{ak})$
1	(0.70, 2.9)	-
2	(0.99, 3.2)	-
3	(1.53, 3.75)	(1.57, 3.63)
4	(1.56, 3.71)*	(1.66, 3.63)
5	(1.71, 3.83)	(1.71, 3.83)
FITB, FITA	238.38	101.26
FIT	339.64	

Table 2. The parameter settings and value of fitness function for second experiment with Re-planning Agent

States	Amplitude and frequencies values for states	
	Planned path $(A_k, f_{ak})$	Re-planned path $(A'_k, f'_{ak})$
1	(0.36, 0.73)	-
2	(0.76, 3.17)	(0.79, 3)
3	(1.22, 3.68)*	(1.29, 3.7)
4	(1.50, 3.69)	(1.31, 3.73)
5	(1.66, 3.84)	(1.66, 3.84)
FITB, FITA	115.49	255.44
FIT	370.92	

3.75) to continue the assembly process with another optimal assembly vibration parameter stage set value (1.57, 3.63) (re-planned path in Table 1). New transition action is made from this new optimal value from the current state with a minimal path distance towards optimal vibration parameter stage set in next state (1.66, 3.63) until it reaches the final point in the assembly simulation process. Table 2 presents the experimental results, where the jamming has occurred in the third stage.

When calculating total fitness *FITT* for these stages, the cost of returning to previous phase was excluded, so the fitness consist from two parts: fitness value before jam *FITB* (from start point to last feasible point) and fitness value of the new path *FITA* that was re-planned after the jam (from new start point to end point). This way, the fitness values can be compared with the values where no jamming occurred.

Figure 11 and Figure 12 show graphical demonstration of the experiments.

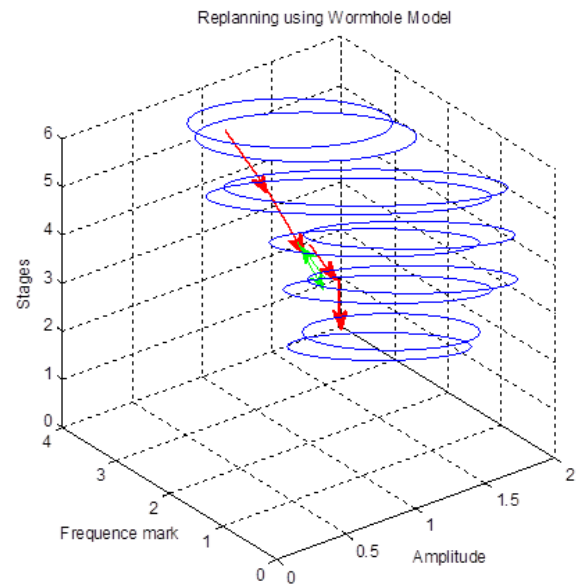


Fig. 11. Result of re-planning process for all 5 stages for first experiment

## 7 CONCLUSION

High-precision robot assembly tasks cannot be successfully done without taking into account the effect of uncertainties. For the robot assembly, the different solutions were used: compliant motion control, cognitive algorithms, adaptive search strategies and intelligent based strategies.

The main contribution of this paper is solving tolerance compensation’s problem in robot assembly using the novel model of hybrid automaton inspired by the Wormhole Model (WOMOLERE), which involves both learning algorithm and re-planning search strategy. The experimental setup was the complex assembly of cogged tube over multistage planetary speed.

The supervised neural network based learning is used to generate wider scope of vibration state parameters of the robot vibration module in order to accommodate the uncertainty in the complex assembly of cogged tube over planetary gears. The genetic based strategy is used to reach the goal assembling point with minimum function costs using the wormhole state solutions. The results show that this approach can satisfactorily resolve the complex problem of tolerance compensation under uncertainty.

While a robot can be programmed to be an expert at a single assembly problem, generalizing this expertise across all assemblies is difficult. Our approach could be easily scalable for other applications, for example robot surgery assistance methods, especially in soft-robotics.

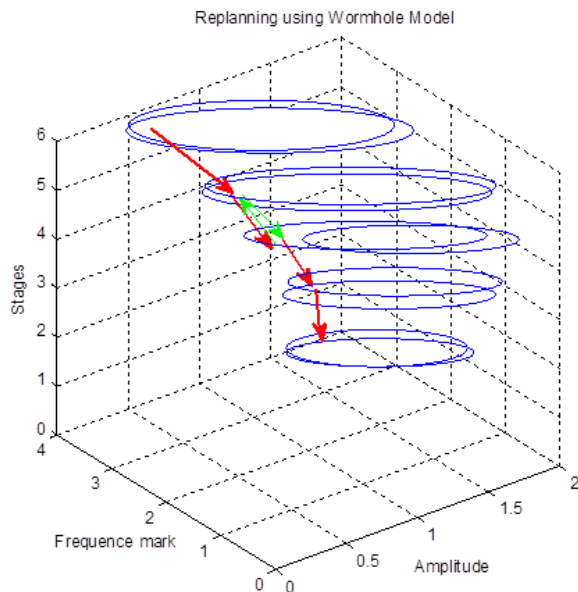


Fig. 12. Result of re-planning process for all 5 stages for second experiment

## REFERENCES

- [1] S.M.Lavalle, *Planning Algorithms*, Cambridge University Press, 2006.
- [2] O. Adria, H. Streich, J. Hertzberg, "Dynamic re-planning in uncertain environments for a sewer inspection robot", *International Journal of Advanced Robotic Systems*, vol. 1, no.1, pp. 33–38, 2004.
- [3] J.F. Zhang, X.T. Nguyen, R. Kowalczyk, "Graph-based multiagent re-planning algorithm", in *AA-MAS'07: Proceedings of the 6th international joint conference on Autonomous agents and multiagent systems*, pp. 1–8, 2007.
- [4] J. Xiao, R. Volz, "On Uncertainty Handling for Assembly Tasks Using Robots," *Robotics and Intelligent Systems*, (C.Y. Ho and G.W. Zobrist, Editors), Vol. 3, ABLEX, pp. 225-260, 1995.
- [5] T. Lefebvre, J. Xiao, H. Bruyninckx, et al., "Active Compliant Motion: A Survey", *Advanced Robotics*, 19:5, pp. 479-499, 2005.
- [6] J. Marvel, J. Falco, "Best Practices and Performance Metrics Using Force Control for Robotic Assembly", National Institute of Standards and Technology, 2012.
- [7] D. Gravel, F. Maslar, G. Zhang, et al., "Toward Robotizing Powertrain Assembly" in *Proceedings of the 7<sup>th</sup> World Congress on Intelligent Control and Automation*, pp. 541-546, 2008.
- [8] I. S. M. Khalil, E. Globovic, A. Sabanovic: "High Precision Motion Control of Parallel Robots with Imperfections and Manufacturing Tolerances", In *Proceedings of the 2011 IEEE International Conference on Mechatronics*, Turkey, 2011.
- [9] C. Brecher, T. Breitbach, S. Muller, M. Ph. Mayer, B. Odenthal, C. M. Schlick, W. Herfs "3D Assembly Group Analysis for Cognitive Automation", *Journal of Robotics*, Volume 2012, Hindawi Publishing Corporation 2012.
- [10] Y. Li, J. Keesling, J. English, et al., "Design, Creation, and Validation of a Comprehensive Database Infrastructure for Robotic Grasping" in *Proceedings of the IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechanics*. pp. 335-341, 2008.
- [11] W.S. Newman, Y. Zhao, Y. Pao, "Interpretation of Force and Moment Signals for Compliant Peg-in-Hole Assembly" in *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 571-576, 2001.
- [12] J.A. Marvel, W.S. Newman, D.P. Gravel, et al., "Automated Learning for Parameter Optimization of Robotic Assembly Tasks Utilizing Genetic Algorithms" in *Proceedings of the IEEE International Conference on Robotics and Biomimetics*, pp. 179-184, 2008.
- [13] J. Wei, W.S. Newman. "Improving Robotic Assembly Performance through Autonomous Exploration" in *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 3303-3308, 2002.
- [14] L. Brignone, K. Sivayoganathan, V. Balendran, M. Horwarth, "Contact localisation: a novel approach to intelligent robotic assembly", in *Proceedings of International Joint Conference of Neural Networks*, pp. 2182–2187, 2001.
- [15] W.S. Newman, M. Branicky, J-H. Pao, "Intelligent Strategies for Compliant Robotic Assembly", in *Proceedings of 11<sup>th</sup> Yale Workshop on Adaptive and Learning Systems*, pp. 139–146, 2001.
- [16] L. Banjanovic-Mehmedovic, "Robot Assembly of Planetary Motor Speed Reducer", in *Proceedings of the VIII IEEE Electrotechnical and Computer Science Conference ERK '99*, Slovenia, pp. 267–270, 1999.

- [17] L. Banjanović-Mehmedović, S. Karic, F.Mehmedovic: "Optimal Search Strategy of Robotic Assembly based on Neural Vibration Learning", *Journal of Robotics, the special issue "Cognitive and Neural Aspects in Robotics with Applications 2011"* Novembar, 2011.
- [18] A. Vodencarevic, O. Niggemann, A. Maier, „Using Behavior Models for Anomaly Detection in Hybrid Systems”, in *Proc. of 23rd International Symposium on Information, Communication and Automation Technologies-ICAT 2011*, Sarajevo, Bosnia and Herzegovina, 2011.
- [19] R. Grosu, S. Mitra, P. Ye, E. Entcheva, I. V. Ramakrishnan, S. A. Smolka, “Learning cycle-linear hybrid automata for excitable cells”, in *Proc. of HSCC07, the 10th International Conference on Hybrid Systems: Computation and Control*, volume 4416 of LNCS. Springer Verlag, , pp. 245–258, 2007.
- [20] O. Niggemann, A. Maier, A. Vodencarevic, B. Jantscher, “Fighting the modeling bottleneck - learning models for production plants,” in *MBEES - Model-Based Development of Embedded Systems*, 2011.
- [21] S. Ekvall, D. Kragic, “Robot learning from demonstration: A Task-level Planning Approach”, *International Journal of Advanced Robotic Systems*, vol.5, no.3, pp. 223-234, 2008.
- [22] S. Schaal, CA. Atkenson, “Learning Control in Robotics”, *IEEE Robotics and Automation Magazine*, vol. 17, no.2, pp. 20–29, 2010.
- [23] N.T. Siebel, Y. Kassahun, “Learning Neural Networks for Visual Servoing using Evolutionary Methods”, in *Proc. of Sixth Inter. Conferences on Hybrid Intell. Solutions, IEEE HIS 06*, 2006.
- [24] J. Tani, R. Nishimoto, J. Namikawa, M Ito, “Codevelopmental Learning between Human and Humanoid Robot Using a Dynamic Neural-Network Model”, *IEEE Transaction on Systems, Man and Cybernetics*, vol. 38, no.1, 2008.
- [25] A. Elshamli, H. A. Abdullah, S. Areibi, “Genetic algorithm for Dynamic Path Planning”, in *Proc. Canadian Conf. Elect. and Comput. Eng.*, Niagara Falls, vol. 2, pp. 677–680, 2004.



**Lejla Banjanovic-Mehmedovic** received the B.S. degree in 1989. and the M.S. degree, in 1999. in automatic control and electronic both from the University of Sarajevo, Faculty of Electrical Engineering, Bosnia and Herzegovina and Ph.D. degree in electrical engineering, from the University of Zagreb, Croatia, in 2006. She worked in Energoinvest, Sarajevo as a software development researcher for supervisory control of industrial real-time systems during period 1989-1994. Since 1995, she has been at the Faculty of Electrical Engineering, University of Tuzla, Bosnia and Herzegovina. Her current research interests include intelligent system's control, mobile robotics, hybrid automata and real-time systems. Since 2010, Associate Professor Banjanovic-Mehmedovic has been a IEEE senior member.



**Fahrudin Mehmedovic** received the B.Sc. degree (Automatics and Electronics) from the University of Sarajevo in 1989. and M.Sc. from University Tuzla, Faculty of Electrical Engineering, Bosnia and Herzegovina in 2004. He worked as a reasercher of Intelligence Process Interface during period 1989-1994 in Energoinvest Sarajevo. In period 1995-1998 he was assistent on University of Tuzla. Since 1998, he has worked in ABB Ltd Representation for Bosnia and Hrzegovina as Product Marketing Manager. He is currently working toward Ph.D. degree at University of Zagreb, Croatia. His current research interests include power electronics and electrical machines control, intelligent control systems and robotics. Mr. Mehmedović is a member of IEEE Control Society and IEEE Industrial Electronic Society.



**Ivan Bosankic** received B.S. of Electrotechnics graduate degree at University of Tuzla, Bosnia and Herzegovina in 2004. He works as a Project Egeiner for electrical drives at IVL d.o.o. company in Tuzla, Bosnia and Herzegovina. He is currently working toward M.Sc. degree at Department for Power Conversion Systems at University of Tuzla. His research interests include electrical drives, power electronics, intelligent systems and adaptive and robust control systems.



**Senad Karic** received B.S. graduate degree in electrical engineering from Tuzla University at 2011. He is currently working at H&H Inc. as Senior Developer (Team lead). His research interests include: MVC and MVVC patterns, Test driven development, Android, Bing Maps development, Spatial data clustering, Spatial databases, Neural Networks.

#### **AUTHORS' ADDRESSES**

**Assoc. Prof. Lejla Banjanovic-Mehmedovic, Ph.D.**  
**Department for Automation,**  
**Faculty of Electrical Engineering,**  
**University of Tuzla,**  
**Franjevačka 2, 75000 Tuzla, Bosnia and Herzegovina**  
**email: lejla.mehmedovic@untz.ba**

**Fahrudin Mehmedovic, M.Sc.**  
**ABB Representative,**  
**Sjenjak 1/222, 75000 Tuzla, Bosnia and Herzegovina**  
**email: fahrudin.mehmedovic@hr.abb.com**

**Ivan Bosankic, B.S.**  
**IVL, Marsala Tita 155, 75000 Tuzla, Bosnia and Herzegovina**  
**email: ivan.bosankic@ivl.ba**

**Senad Karic, B.S.**  
**H&H Inc., Trg Stara Trznica 8, 75000 Tuzla, Bosnia and Herzegovina**  
**email: senad.karic@hhinc.eu**

Received: 2012-06-29

Accepted: 2013-04-11