Biomimetic Intelligence in Robotics

Kazuo Ishii and Hiroyuki Miyamoto
Dept. of Brain Science and Engineering, Kyushu Institute of Technology
2-4 Hibikino, Wakamatsu, Kitakyushu, Fukuoka, 808-0196 Japan
email: {ishii, miyamo}@brain.kyutech.ac.jp

Abstract - The Kyutech COE program "World of brain computing interwoven out of animals and robots" launched in 2003. The main objective of the program is to establish new information technology by imitating the processing system in brain and nervous system, and learning the formation mechanism of behaviors. The robotics research group at the Kyutech COE takes charge of the application of biomimetic intelligence into robotics. In this paper, we introduce three biomimetic intelligence topics, which are (i)Central Pattern Generator (CPG) for bipedal walking, (ii)Self-Organizing Map (SOM) for environment recognition and navigation of mobile robots, and (iii)Task Optimization in the Presence of Signal-dependent noise (TOPS(a)) model for trajectory planning.

I. Central Pattern Generator For Bipedal Walking

A. Bipedal walking

The intelligence of robot is widely recognized as the product of the interaction between the artificial intelligence and physical capabilities. Based on the idea, the various humanoid and bipedal walking robots have been developed and the possibilities of humanoid robots are examined with simulations and experiments. In order to realize the bipedal walking, there are many problems to overcome, such as motion control, torque control, development of new actuators, and so on. Locomotion control is one of the most important problems to be solved, and well-known control method "ZMP [1]" has been proposed to compensate rolling and pitching moments. Though human beings do not care about such compensation, the smooth bipedal walk is realized. The rhythm generator mechanism called Central Pattern Generator (CPG) [2][3] has been proven to be involved in rhythmic activities, such as locomotion, respiration, heartbeat, etc. The locomotion employing Central Pattern Generator (CPG) attracts attention, because both a nervous system and a musculo-skeletal system have interaction with each other, and the oscillatory dynamics is achieved with CPG networks.

CPG is a model to represent mutual inhibition among neurons, such that a neuron's excitation suppresses others neurons' excitations. Matsuoka[4] proposed a mathematical model, and gave some mathematical conditions for mutual inhabition networks represented by a continuous-variable neuron model to generate oscillation. Taga et. al. [2][3] proposed a principle of adaptive control of locomotion system, where nervous, musculo-skeletal, and sensory systems behave cooperatively to adapt to unpredictable environments. The results of bipedal walk in 2-D simulation show robustness against the change of slopes. Miyakoshi et. al. [5] expanded the 2-D simulation to 3-D motion, and the stable stepping simulation was realized in the simulations. Hase et. al. [6] proposed a parameter optimization method using Genetic Algorithm (GA), and analyzed the 3-D motion with a precise musculo-skeletal system and a hierarchical nervous system. Also, the motion control method using nonlinear oscillators have been proposed and verified by quadruped robots [7][8][9] and hexapod robot [10][11].

This paper describes a CPG parameter searching method with GA to obtain the CPG parameters efficiently [12], which has five steps corresponding to the target joints. The outputs of the CPG network represent the target joint angles, and the bipedal walking simulation is discussed and examined using the CPG network and feedback signals from a touch sensor at foot. The simulation model is constructed using a motion analysis software, DADS [13], and the control system of bipedal walk is constructed with MATLAB/Simulink.

B. Parameter optimization with genetic algorithm

CPG is a model of biological rhythmic system, and consists of some neural oscillators where mutual inhibition among neurons is modeled such that a neuron's excitation suppresses other neurons' excitations. In this paper, the mathematical model of CPG proposed by Matsuoka [4] is introduced into the locomotion of a bipedal robot. The model among n neurons with adaptation is expressed as shown in (1).

$$\begin{aligned} T_u du_i / dt &= -u_i - \beta v_i - \sum_{j=1}^{n} w_{ij} y_j + u_0 + feed_i \\ T_v dv_i / dt &= -v_i + y_i \\ y_i &= \max(0,\ u_i) \end{aligned} \tag{1}$$

Here, u_i is a membrane potential of the i-th neuron, v_i is the variable that represents the degree of the adaptation, T_u, T_v and β are the parameters that specify the time constant for the adaptation, the w_{ij} indicates the strength of the inhibitory connection between the neurons. u_0 is an external input with a constant rate, and $feed_i$ is a feed back signal and discussed e.g., in [14][15]. The mathematical conditions to generate oscillations are analyzed precisely in [4]. An attractive feature is that the CPG can adapt to external signals from the sensory system, the nervous system and the unpredictable environment. The outputs of CPG return to the rhythmical oscillation with the same frequency if the external signals are removed. The CPG network for bipedal walk is designed to have an oscillator with two neurons, which are an extensor neuron and a flexor neuron, on each joint. The output signals of the neural oscillators are used as target angles of the corresponding joints. The parameters in (1), T_u, T_v, β and w_{ij} are optimized using Genetic Algorithm (GA).

C. Parameter optimization with Genetic Algorithm

In order to obtain a target time series of the joint angles, the angles of ankle, knee, hip and waist joints are measured using a real-time motion capture system. Genetic algorithms are introduced to search the parameters of CPG network in Fig. 1. Genetic algorithm is an optimizing algorithm based on the mechanics of natural selection and natural genetics and applied to various kinds of optimization problems [8].

In the CPG network in Fig. 1, there are 271 parameters to search. It is difficult to find all parameters at once, therefore, the optimization process is divided five steps as shown in Fig. 1; (i) parameters of two hip joints, (ii) two hips, a knee and an ankle joint of the left leg, (iii) the lower body network, (iv) the upper body network, and (v) the total network.

The strategy of GA is as follows.

Selection: The outputs of CPG network will change widely by the subtle change of parameters. Therefore, an elite strategy is applied in order to preserve the individuals with high scores in the successive generations. Comparing the highest evaluation values changing the rate of elite 0% to 50% at (1), the rate of elite 10% is selected. The rest of individuals (90%) are selected by a roulette strategy based on the evaluation value at random.

Crossover: The two-point-crossover is used, and a right point is in the right half region and a left point in the left region. The central part between the two points is exchanged with the probability of 80 %.

Mutation: The probability of mutation is 0.5%.

Coding: Each parameter is expressed in 12 bits, and one bit corresponds to 0.003. The parameters are within [-6.141, 6.141]. And the number of individuals in one generation is 500.

Evaluation: The evaluation value is given as the difference between the target joint angles and the output of CPG network.

At the first step (i), the parameters of the hip joints are calculated, and the comparison of structures with and without a self- recurrent connection is performed, and we decided not to use the self-regressions in neurons from the results. Consequently, the self-regressions of each neuron are not used in the following four steps. (ii) Secondly, the parameters of hip joints, a knee joint and an ankle joint of the right leg are calculated based on the hip parameters obtained from the step (i). The two structures, the bidirectional connections among the hips, a knee and an ankle neurons, and unidirectional connections are compared. The parameters for the hip joints are inherited from those of step (i). And small random values within the range of [-0.045, 0.045] [rad] are added. The other parameters take random values within [-6.141, 6.141]. The result shows that the CPG network with unidirectional connections can express the target joint angles as same as with bidirectional connections. (iii) Next, the parameters of the lower body are calculated using the result of (ii). The structure is designed to have a symmetric structure. (iv) The parameters of the upper body and the connections between the waist joints and the hip joints are obtained. The connections between left and right hip joint take the same values as those in (iii). (v) Finally, the total parameter optimization is carried out using the those of (iii) and (iv). The parameters which can output the similar oscillations close to the target joints angles are obtained by dividing the optimizing process into five steps. The obtained parameters, and the trajectories of each joint and the output of CPG are described in [12]. The parameters are introduced to the bipedal walk simulations, and feedback signals from touch sensors on foot are fed to the variables $feed_i$ The results show the effectiveness of the present approach.

II. SELF-ORGANIZING MAP FOR ENVIRONMENT RECOGNITION AND NAVIGATION OF MOBILE ROBOTS

A. Self-Organizing Map (SOM)

Self-Organizing Map (SOM) is one of the topologically correct feature maps proposed by Kohonen[16] and known as one of attractive method to extract the characteristics in data and to classify data into clusters through its self-organizing process. Brains of many higher animals appear to achieve topological relationship through a stream of sensory inputs,

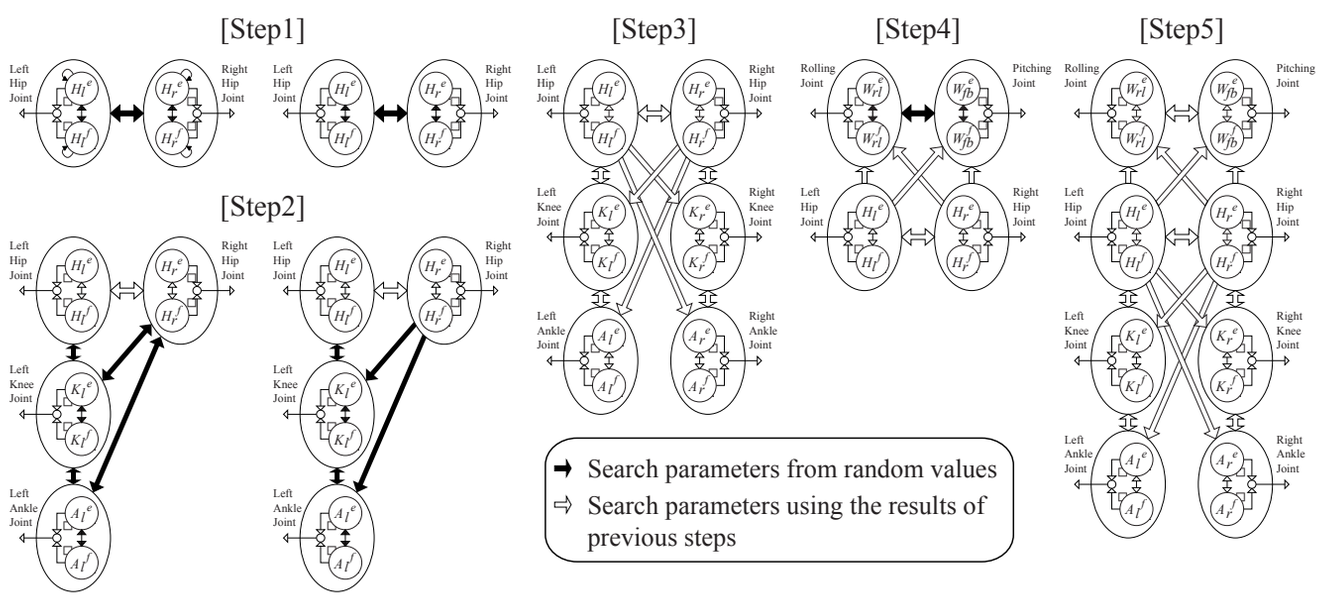

Fig. 1. The CPG network for bipedal walk. Each circle means a neural oscillator, giving a target joint angle. The optimization process is divided into five steps.

and several algorithms have been suggested to account for the neural processing. The SOM has the algorithm which is capable to establish the feature map from learning a random sequence of input samples. The Kohonen's algorithm can be represented in a simple iterative form, therefore, the algorithm demonstrates its capability with computational power.

In the field of robotics, the SOM attracts attention as an efficient tool to realize robot intelligence, e.g, Ritter and his group have been investigating the research on the direct experimental approaches to elucidate the architecture of higher brains associated with the possibilities and limits of artificial control architectures for robot systems [17]. And the techniques of SOM are applied into problems such as posture analysis[18], self-location[19], collision avoidance, path planning and so on [20], and the results show the robustness and adaptability.

We have been investigating the application of neural network technology into the Autonomous Underwater Vehicles (AUVs) focusing on the capability of neural networks such as learning, nonlinear mapping. Underwater vehicles are expected as the attractive tools for the operation in the extreme environment such as the deep ocean survey. In order to realize the useful and practical robots which can work in the ocean, underwater vehicles should take their action by judging the changing condition from their own sensors and actuators, and are desirable to make its' behaviors with limited efforts of the operators, because of features caused by the working environment. Therefore, the mobile robot should be autonomous and adaptive to their environment. Considering the above features, we proposed an adaptive control system and a collision avoidance system[21].

Development of the navigation system which can navigate the vehicle without the collision to the obstacles is one of the most important problems in order to realize the AUVs. In this paper, Self-Organizing Map (SOM) proposed by Kohonen are applied to the navigation system which takes the distances to the surroundings as inputs, and outputs the direction for the robot to proceed. The efficiency of the system and the adaptive learning method for navigation are investigated through the simulation and experiments with an underwater vehicle Twin-Burger [22].

Here gives a brief account of Kohonen's algorithm.The algorithm describes a map from an input space V into an output space A. The output space consists of nodesj, which are usually arranged in vertices of a two-dimensional lattice. For each node j in A, a reference (weight) vector mi is assigned, and the same input vector x in V is broadcasted to all of the nodes in A. The best-matching node, the "winner" node is defined according to (2).

$$\|x - m_c\| = \min_i \{\|x - m_i\|\} \tag{2}$$

$$\begin{aligned} m_i(t+1) &= m_i(t) + \alpha\left[x(t) - m_i(t)\right] \quad && \forall i \in N_c(t) \\ m_i(t+1) &= m_i(t) && \forall i \notin N_c(t) \end{aligned} \tag{3}$$

The winner node m_c are selected by referring to an arbitrary norm, here, the Euclidean norm in the input space V. Updating of m_i is restricted to a topological neighborhood Nc of the winner node m_c, and the weights are updated with (3).

B. Environment recognition

An enviornment recognition based on SOM is described here. The target underwater robot is equipped with 6 ultrasonic range sensors in the horizontal plane, to measure the distance to the obstacles, and the sensors are set in backward, rightward, right-forward, leftward, left-forward and forward. The enviornment recognision system estimtes robot's situation based on obtained learning results, "map" in Fig.2, based on typical locations. The teaching data x consists of distances r_i (i=1~6), and t_x, t_y the target direction expressed in the vector form of x-y coordinate.

The teaching data $\boldsymbol{x}$ include the inputs from the sensors and outputs to the control system (the target direction). Therefore, the mapping function, the relationship between the situation of robot and the action, can be acquired through the learning process. This kind of network is proposed by Yamakawa, et. al, and called as SOR (Self-Organizing Relationship) network [23]. The learning process in the conventional SOM is regarded as the unsupervised learning. In the SOR, as the network learns the function between inputs and outputs, it can be easily extended to the supervised learning.

C. Results of learning and behavior of a robot

The obtained map consists of 40 x 40 nodes. The boundaries are clearly observed and some clusters are constructed in the map. The robot takes an action by finding the best-matching node in the map. It is shown that if the location of robot is in the upper side of the map, the robot tends to go forward, and if in the lower side, go back. And the robot will turn right if the location of robot is in upper-right of the map, and turn left if the robot is in the lower-right and left part of the map.

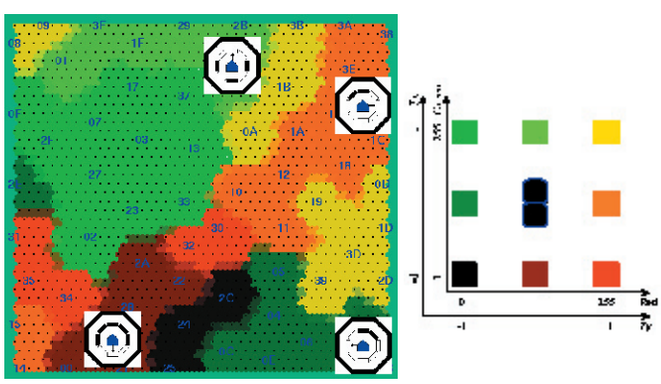

Fig.2 Results of learning from the basic rules, "Map". The target direction in the left figure is colored using the color arrangement in the right figure.

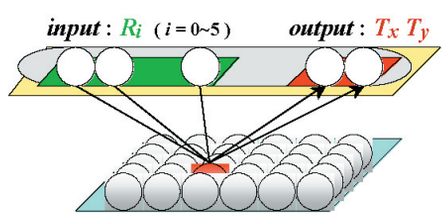

Fig.3 The output data t_x and t_y are obtained as the last the two values of the winner node which is selected based on input r_i.

The winner node is selected by computing the Euclidean norm between the measured distances and r_i and then, the target direction, the heading of the robot, is defined with the parameters t_x, t_y in the winner node (Fig.3).

D. Simulation and experiment with map

The simulation is that the robot goes around the maps and avoids the collision. The results of the simulation are shown in the Fig. 4. In the figure, the black area means the vacant space which the robot can transit freely, and the area depicted in the light color expresses the walls and obstacles, and the white square is the robot. The trajectories of the robot are drawn in the white lines. The robot simulator calculates the distances as the pixel number from the center of robot to the first light pixel within the range of 30 degrees for the each direction. The robot can move without a collision in the simulation. The robot tends to transit in the forward direction and turn left in the corner, this property is caused by the target direction of the input data.

The proposed navigation system with the Map is investigated with an underwater robot Twin-Burger. The Twin-Burger is an autonomous underwater vehicle designed as a versatile test bed for software development. The experiments are carried out in a circular pool with the diameter of 6 [m]. The detail of experimental results are in [24]. The results shows that the underwater robot can move without the collision, and takes the designed actions. This system symbolizes the local condition of the robot in 2-D plane and makes decision of the robot.

III. Task Optimization In The Presence Of Signal-Dependent Noise (TOPS(α)) Model

A. Trajectory planning models

In the conventional trajectory planning models such as minimum jerk model[26], minimum torque change model[27], minimum commanded torque change model[28], minimum variance model[29], the boundary condition (position, velocity and acceleration of the start and end points) must be specified to solve a constrained nonlinear optimization problem.

In the TOPS(α) model the trajectory planned so as to maximize task achievement $\boldsymbol{T}_A$ and minimize energy consumption in the objective function

.

Fig. 4 Results of simulation with the Map.

$$C_T = (1 - T_A) + \alpha \frac{\int_0^{t_e} \sum_{j=1}^{N} \tau_j^{\,2} dt}{t_e} \tag{4}$$

The task achievement $\boldsymbol{T}_A$ is a function of the probability that the hand is in the target region. It is not necessary to specify the boundary condition. Because of the signal-dependent noise, the smoothness is implicit in the minimum variance and the TOPS(α) model. Simulation result showed that an additional constraint (e.g. minimum energy) must be required.

B. Experiment

So far, the hand trajectories were mainly measured in point-to-point movements. In this experiment the target is not a stationary point but a moving disk.

Figure 5**a** shows the experimental setup. The experiment was performed as follows;

(1) Figure 5**b**: the subject set his hand at the start position.
(2) Figure 5**c**: the subject moves his hand toward the right direction at a sign from the experimenter.
(3) Figure 5**d**: After ballistic movement time t_f=0.5 [sec.]), the target circle (diameter D_T=0.05[m]) appears at the 0.3 [m] rightward from the start position and start to move at constant acceleration. After the tracking movement time (t_e=1 [sec.]), the target return the initial position and disappear.
(4) The subject instructed to keep the cursor in the target circle while the target is displayed (form the time t_f to t_e).

C. Comparison between experimental data and numerical prediction

Figure 6 shows the ballistic part of the trajectories (time 0 to t_f) of the subject and models. The dotted lines are mean hand trajectories of eight subjects. TOPS(α=0) denotes the maximum task achievement without minimum energy consumption. TOPS(α=5) denotes the maximum task achievement with minimum energy consumption. MCTC, MTC, and MJ denote the minimum commanded torque change, the minimum torque change, and the minimum jerk models, respectively.

We must specify the boundary condition accurately in the case of the conventional models. In this experiment, for the boundary condition, we used the the movement of the center of the target at the end time of the ballistic movement (t_f =0.5 [sec.]) (initial velocity v_{x0},v_{y0})=(0,0.8), constant acceleration (a_x, a_y)=(0,-3.2)). As shown in the figure 3, the TOPS(α) model predicted convexed trajectories that agreed well with trajectories of subjects.

D. TOPS(α) model

We propose a new framework for wide variety of motor control: the TOPS(α) (Task Optimization in the Presence of Signal-dependent noise) model. The optimum criterion of this model is combination of the maximum task achievement

and the minimum energy consumption. We showed that the trajectories predicted by this model agree well with that of human subjects in the case of the moving target. To verify the TOPS(α) model, quantitative examinations must be done in the near future.

IV. Conclutions

In this paper, the three biomimetic intelligent technologies are introduced and applied to robotics. This kind of technique has the possibility to establish new and inovative infomation processing methods. We expect that robots with flexible silicon brain are realized and make our society more comfortable living space.

References

[1] A.Takanishi, "Biped Walking Robot Compensating Moment by Trunk Motion", RSJ Vol.11 No.3, pp348-353,(1993)

[2] G.Taga, Y.Yamaguchi, H.Shimizu, "Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment", Biol. Cybern. vol.65, pp.147-159 (1991)

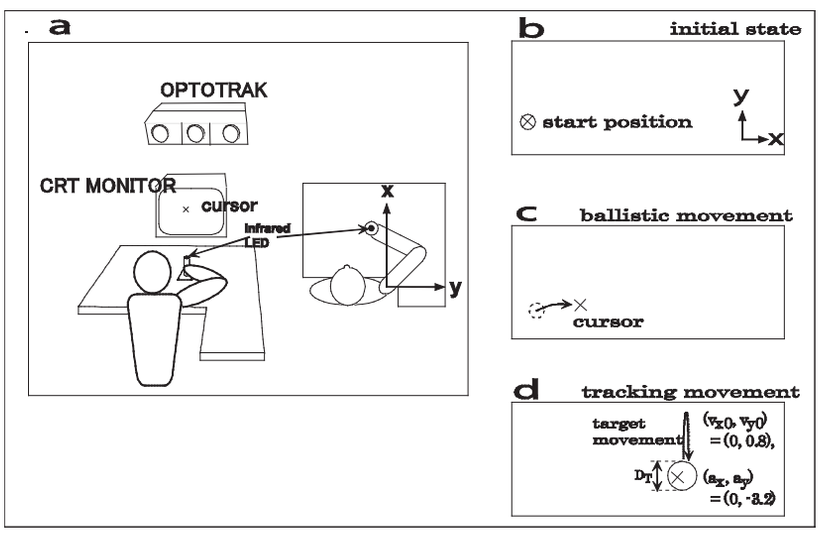

Fig. 5 Experimental setup to measure the trajectories of human hand.

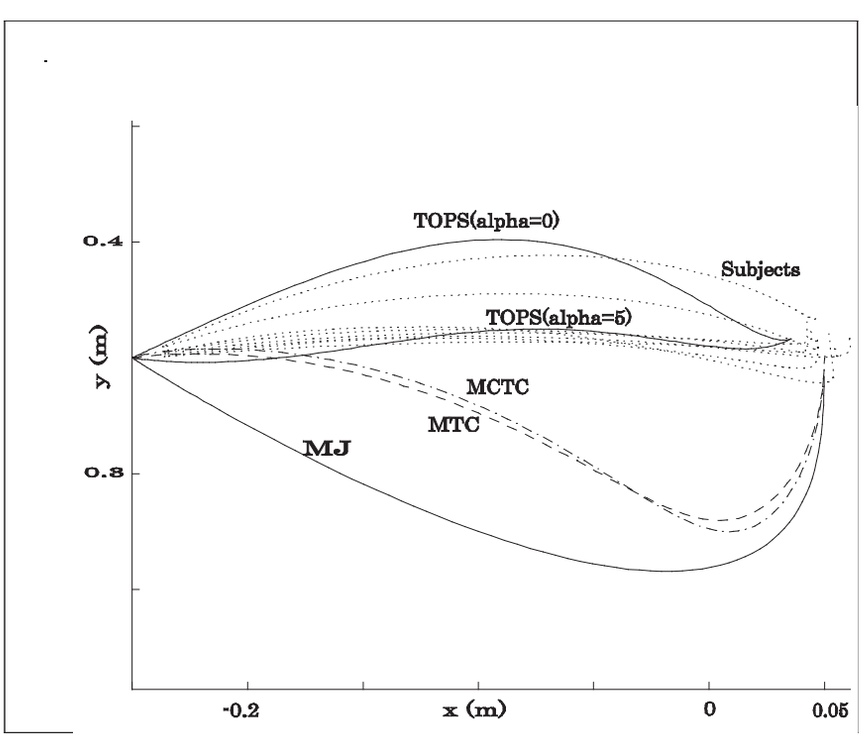

Fig. 6. Hand trajectory of eight subjects and each model. Dotted lines show mean trajectories from eight subjects. TOPS(alpha=0), TOPS(alpha=5), MCTC, MTC, MJ represent TOPS, TOPS with minimum energy consumption,, minimum commanded torque change, minimum torque change, minimum jerk models, respectively.

[3] G.Taga, “Modeling and Simulation of Bipedal Locomotion”, J. of Society of Biomechanisms of Japan,vol.16, no.3, pp.209-214 (1992)
[4] K.Matsuoka, “Mechanisms of Frequency and pattern control in the neural rhythm generators”, Biol. Cybern.vol.56, pp.345-353 (1987)
[5] S.Miyakoshi, G.Taga, Y.Kuniyoshi and A.Nagakubo, “Three Dimensional Bipedal Stepping Motion using Neural Oscilltors”, J. of RSJ, vol.18, no.1, pp.87-93 (2000)
[6] K.Hase, N.Yamasaki, ”Synthesis of bipedal motion resembling actual human walking by neural oscillators and genetic algorithms”, J. of SICE, vol.33, no.5, pp.448-454 (1997)
[7] H.Kimura, S.Akiytama and K.Sakurama,”Realization of dynamic walking and running of the quadruped using neural oscillator”, Autonomous Robots, vol.7, no.3, pp. 247-258 (1990).
[8] W.Ilg, J.Albiez, H.Jedele, K.Berns and R.Dillmann,”Adaptive periodic movement control for the four legged walking machine BISAM”, Proc. Of ICRA1999, pp.2354-2359 (1999)
[9] K.Tsujita, K.Tsuchiya and A.Onat,”Adaptive Gait Pattern Control of a Quadruped Locomotion Robot”, Proc. Of IROS2001, pp.2318-2325 (2001)
[10] H.Cruse, D.E.Brunn, Ch.Bartling, et al.,”Walking: A complex hevavior controlled by simple networks”, Adaptive Behavior, vol.3, no.4, pp.385-418 (1995)
[11] K.Akimoto, S.Watanabe and M.Yano,”An insect robot controlled by emergence of gait patterns”, Proc. of AROB, vol.3, no.2, pp.102-105 (1999)
[12] H.Inada, K.Ishii, “Behavior Generation of Bipedal Robot Using Central Pattern Generator (CPG), 1st report: CPG Parameters Searching Method by Genetic Algorithm”, Proc. of IROS2003, pp. 2179-2184 (2003)
[13] Edward J. Hang, “Computer Aided Kinematics and Dynamics of Mechanical Systems”, Volume 1, Basic Methods Computer Aided Design Software, INC. (1989)
[14] T.Yamasaki, T.Nomura, S.Sato, “Possible functional roles of phase resetting during walking”, Biol. Cybern., vol.88, pp. 468-496 (2003).
[15] K.Tsuchiya, S.Aoi and K.Tsujita,”Locomotion Control of a Biped Locomotion Robot using Nonlinear Oscillators”, Proc. of IROS2003, pp.1745-1750 (2003)
[16] T. Kohonen, “Self-organized formation of topologically correct feature maps”, Biol. cybern., vol. 43, pp. 59-69.(1982)
[17] H. Ritter, et al, “Neural Architectures for Robotic Intelligence”,Rev. Neurosci, (2003)
[18] A.Saalbach G.Heidemann and H.Ritter, “Parametrized SOMs for Object Recognition and Pose Estimation”, Proc. Of ICANN 2002, pp. 902-907,7, (2002)
[19] M.Tsumi and M.Ishikawa, “Development of a simulator for robots and its application to position estimation by self-organization”, Technical Report of IEICE, Vol.100, No.687, NC2000-147, pp.149-156, (2001)
[20] Barreto, G.A., Araujo, A.F.R., Duker, C. and Ritter, H. “A distributed robotic control system based on a Temporal Self-Organizing Neural Network”, IEEE Transactions on Systems, Man, and Cybernetics, C-32(4):347-357 (2002)
[21] K. Ishii, T. Fujii and T. Ura . “An On-line Adaptation Method in a Neural Network Based Control System for AUVs,” IEEE Journal of Oceanic Engineering, Vol. 20 No. 3, pp. 221-228.(1995)
[22] T. Fujii, T. Ura and Y. Kuroda, “Mission Execution Experiment with a Newly Developed AUV The Twin-Burger”, in Proc. 8th UUST, pp. 92-105, (1993).
[23] T.Yamakawa and K.Horio, “Self-Organizing Relationship (SOR) Network,” IEICE Trans. on Fundamentals, Vol.E82-A, pp.1674-167, (1999).
[24] K.Ishii, S.Nishida and T.Ura, “A Self-Organizing Map Based Navigation System for an Underwater Vehicle,” Proc. of IEEE ICRA’04, pp. 4466 - 4471, (2004).
[25] Flash T, Hogan N, “The coordination of arm movements: An experimentally confirmed mathematical model”. Journal of Neuroscience}, 5:1688-1703, (1985).
[26] Uno Y, Kawato M, Suzuki R, “Formation and control of optimal trajectory in human multijoint arm movement - minimum torque-change model,” Biological Cybernetics, 61:89-101, (1989).
[27] Kawato.M, “Optimization and learning in neural networks for formation and control of coordinated movement,” In D.Meyer and S.Kornblum, editors, Attention and Performance, XIV: Synergies in Experimental Psychology, Artificial Intelligence, and Cognitive Neuroscience - A Silver Jubilee}, pp 821-849. MIT Press, Cambridge, MA, USA, (1992).
[28] Harris C M, Wolpert D M,”Signal-dependent noise determines motor planning,” Nature, 394(20):780-784, (1998).