

Soft computing for the intelligent robust control of a robotic unicycle with a new physical measure for mechanical controllability

S.V. Ulyanov, S. Watanabe, V.S. Ulyanov, K. Yamafuji,
L.V. Litvintseva, G.G. Rizzotto

Abstract The posture stability and driving control of a human-riding-type unicycle have been realized. The robot unicycle is considered as a biomechanical system using an internal world representation with a description of emotion, instinct and intuition mechanisms. We introduced intelligent control methods based on soft computing and confirmed that such an intelligent control and biological instinct as well as intuition together with a fuzzy inference is very important for emulating human behaviors or actions. Intuition and instinct mechanisms are considered as global and local search mechanisms of the optimal solution domains for an intelligent behavior and can be realized by genetic algorithms (GA) and fuzzy neural networks (FNN) accordingly. For the fitness function of the GA, a new physical measure as the minimum entropy production for a description of the intelligent behavior in a biological model is introduced. The calculation of robustness and controllability of the robot unicycle is presented. This paper provides a general measure to estimate the mechanical controllability qualitatively and quantitatively, even if any control scheme is applied. The measure can be computed using a Lyapunov function coupled with the thermodynamic entropy change. Interrelation between Lyapunov function (stability condition) and entropy production of motion (controllability condition) in an internal biomechanical model is a mathematical background for the design of soft computing algorithms for the intelligent control of the robotic unicycle. Fuzzy simulation and experimental results of a robust intelligent control motion for the robot unicycle are discussed. Robotic unicycle is a new Benchmark of non-linear mechatronics and intelligent smart control.

Key words Biomechanical model, Soft computing algorithms, Intelligent robot unicycle, Robust control, Posture stability, Controllability, Fuzzy control, Entropy measure of controllability

1 Introduction

In the research of advanced robotics, it is always one of the important fields to emulate some intelligence or capabilities which are inherited by human beings or animals. Considering the locomotive capabilities we all know that human beings and some animals have quite excellent locomotion on walking, running or jumping, and we believe that it is beneficial and helpful to emulate human walking, running or jumping by a robot. In fact, during the last few years some research results have been reported in which a robot could emulate human walking or an animal's running/jumping.

We attempted in the present work the emulation of human riding a unicycle by a robot. It is well known that the unicycle system is an inherently unstable system and both longitudinal and lateral stability control are simultaneously needed to maintain the unicycle's postural stability. It is an unstable problem in three dimensions (3D). However, a rider can achieve postural stability on a unicycle, keep the wheel speed constant and change the unicycle's posture in the yaw direction at will by using his flexible body, good sensory systems, skill and intelligent computational abilities. Investigating this phenomenon and emulating the system by a robot, we aim to construct a biomechanical model of human motion dynamics, and also evaluate the new methods for the stability control and analysis of an unstable system.

Remark 1. Our study of the rider's postural stability control on a unicycle began in 1985 with the observation and analysis of human behavior while riding a unicycle. Although the unicycle's posture stability was attained only for 12–13 s in 1985, its stable driving could not be realized [7, 49]. In 1991 we restarted the investigation of the improved unicycle robot which could emulate the human riding system. Our newly developed model has two significant mechanisms to emulate human motion, one is a two closed-link mechanism equipped with motors at both sides of the wheel and another is an overhead rotor mounted on the body of the unicycle. Both represent to a certain extent the human leg-thighs and shoulders-torso, respectively [29–33]. Then we achieved the first success so far reported in posture stability and driving control of a human-riding-type unicycle robot in 1994 [30–32].

Computer simulations using the dynamical equations of motion of the developed unicycle robot have been carried out according to the proposed control scheme [30, 31, 37]. Furthermore, the experiments have been conducted with the

S.V. Ulyanov, S. Watanabe, V.S. Ulyanov, K. Yamafuji, L.V. Litvintseva
Department of Mechanical and Control Engineering, The University
of Electro-Communication, 1-5-1 Chofugaoka, Chofu, Tokyo 182,
Japan

G.G. Rizzotto
Corporate Advanced System, SGS-THOMSON Microelectronics, Via
C. Olivetti 2, 20041 Agrate Brianze, Italy

Correspondence to: S.V. Ulyanov

proposed fuzzy gain schedule PD-control method [37]. The usage of three rate gyro-sensors installed on the robot for the measurement of the robot's postures in 3D gave us satisfactory results in posture stability and driving. Experimental results [32, 37] show that the robot's longitudinal and lateral postures can be stabilized successfully. Thus, the proposed fuzzy gain schedule PD-control method provides one of the reasonable approaches to handle such a nonlinear problem existing in the unicycle robot system.

This paper generalizes the results of [33, 37–42]. A new biomechanical model of robotic unicycle is developed. We consider the dynamic behavior of the biomechanical model from the standpoint of mechanics, decision-making process, action logic, and information processing with distributed knowledge base levels. The physical and mathematical background for the description of the biomechanical model is introduced. In this paper a thermodynamic approach [23–25] is used for the investigation of an optimal control process and for the estimation of an artificial life of mobile robots [39, 42]. A new physical measure – the minimum entropy production – for the description of the intelligent dynamic behavior and thermodynamic stability condition of a biomechanical model [40, 41] with an AI control system for the robot unicycle is introduced. This measure is used as a fitness function in a GA for the computer simulation of the intuition mechanism as a global searching measure for the decision-making process to ensure optimal control of the global stability on the robot unicycle throughout the full space of possible solutions. The simulation of an instinct mechanism based on FNN is considered as a local active adaptation process with the minimum entropy production in the learning process of the vestibular system by teaching the control signal accordingly to the model representation results of [40]. Unlike [37, 38, 40], computer simulations in this study are carried out by the usage of *thermodynamic* equations for the motion [41, 44] of the robot unicycle. Entropy production and entropy measures for the robot unicycle motion and the control system are calculated directly from the proposed thermodynamic equations of motion. From the results obtained in this study by the fuzzy simulation and soft computing, based on GA and FNN, it is obvious that the intelligent behavior controllability and postural stability of the robot are largely improved by two fuzzy gain schedule PD-controllers in comparison to those controlled only by a conventional PD and a fuzzy gain schedule PD-controller [31–33]. As a result of this investigation the look-up tables for fuzzy robust controllers of the robotic unicycle are formed with minimum production entropy in intelligent controllers and the robotic unicycle model uses this approach.

It is confirmed that the proposed fuzzy gain schedule PD-controller is very effective for the handling of the system's nonlinearity dealing with the robot's posture stability controls. Furthermore, an important result is that the minimum entropy production gives a quantitative measure concerning the controllability and also qualitative explanations. Thus, we provide a *new benchmark* for the controllability of unstable nonlinear nonholonomic dynamic systems by means of intelligent tools [37, 40, 41] based on a new physical concept of robust control, the minimum entropy production in control systems and in control object motion in general.

2 Biomechanical qualitative model and robot model of the unicycle

As it is observed in our previous papers, a human rider's controlling actions on a unicycle using his torso, shoulders and arms are quite complicated. Usually, the rider's posture or altitude is not always symmetric to the wheel's principal axis. In the improved unicycle model [31, 32, 37] two unique and characteristic structures are contrived. One is an overhead rotor (hereafter, rotor) mounted on the torso (body) and another is the double 4-bar closed-link mechanism on both sides of the wheel. These two structures are considered to play an important role in our biomechanical control system.

2.1 Biomechanical control model

Here we propose a hierarchical logic structure of distributed knowledge representation for the artificial life of a robot unicycle as shown in Fig. 1a. The control of human riding unicycle as a logic-dynamic hierarchical process is formed by: 1) a dynamic mechanical system “human riding unicycle”; 2) a decision-making process of unicycle intelligent control with different levels of *skill* operations; 3) a logic behavior for the coordination of the human body and feet based on *intuition, instinct, and emotion* mechanisms; and 4) a distributed information system for cooperative coordination of sub-systems of the biomechanical model [37, 38]. For the description of artificial life of the robotic unicycle we use methods of qualitative physics for internal world representation based on the mathematical model of unicycle motion.

The logic structure of the biomechanical control system for the description of a human riding unicycle include four levels: 1) distributed information levels with sub-levels; 2) logical systems; 3) support decision-making systems; and 4) dynamic mechanical systems.

Distributed information levels include *four* sub-levels: 1) physical level and logic or virtual reality; 2) behavior and coordination level; 3) intelligent control levels with two sub-levels; and 4) executive biomechanical level. Intersections between horizontal lines of distributed information levels and vertical lines of *logic systems, support decision-making systems, and dynamic models* of unicycle motion, and *human behavior* as the biomechanical control system realize the particular models for human riding of unicycle with different skill levels of smart control tools.

For example, an intersection of the first horizontal level (physical level and logic of virtual reality) with the first vertical level (logic systems) results in a learning process structure of control of a human riding unicycle; an intersection with the second vertical level (support decision-making systems) corresponded to the level of the central nervous system as biological control; and an intersection with the third level (dynamic mechanical systems) introduces mechanical models of unicycle motion as a dynamic system. The logic sum of these sub-levels realizes the physical level of unicycle motion description and physical interpretation of data observations and measurements. The mathematical background used for the description of a learning process is the *quantum fuzzy logic* (see below Remark 4). The functions of a central nervous

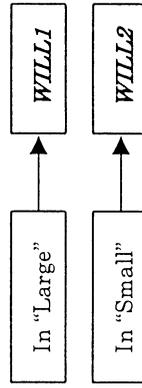
DESTRIBUTED INFORMATION LEVELS



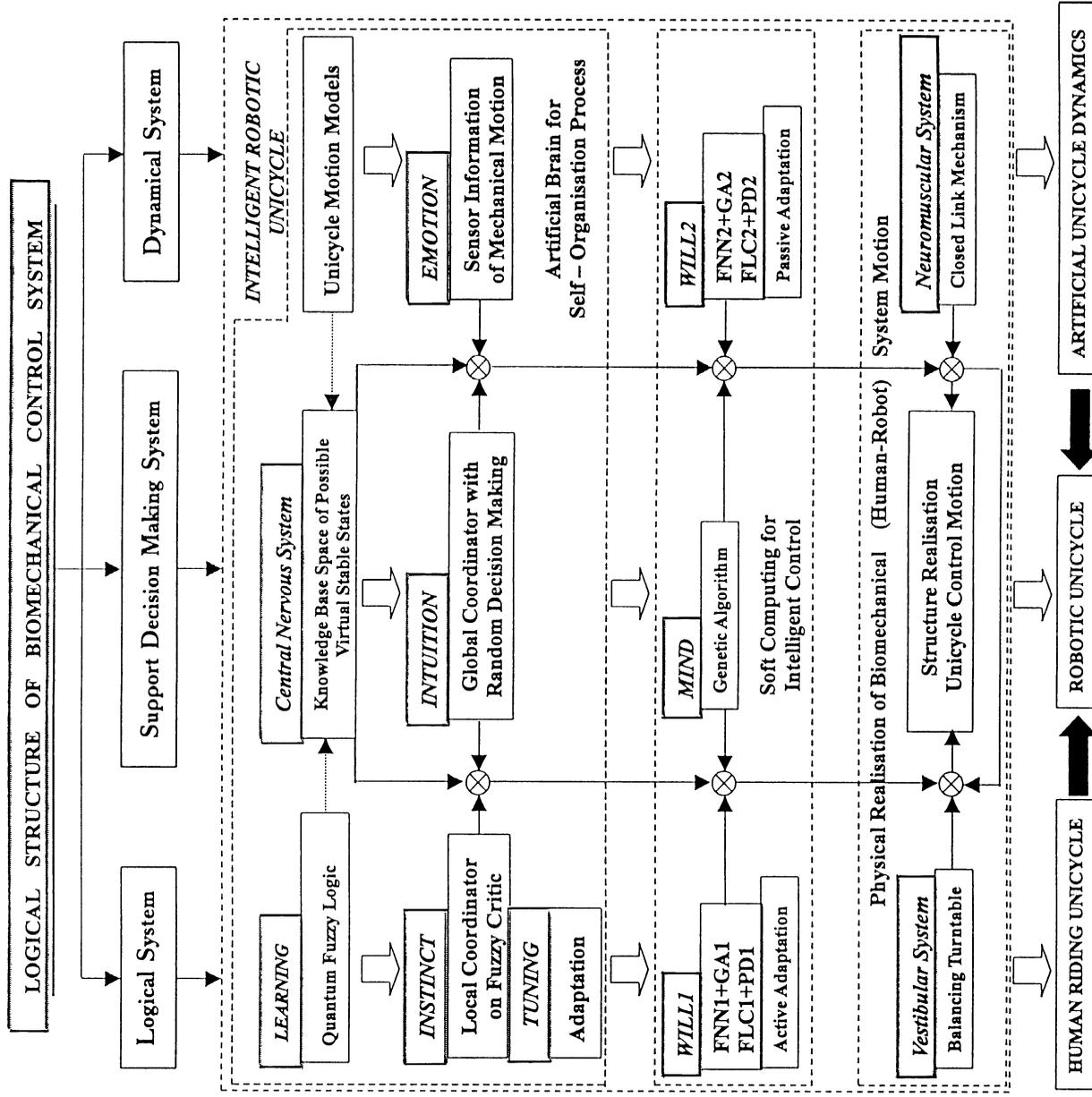
1. Physical Level and Logic of Virtual Reality

2. Behaviour and Coordination Level

3. Intelligence Control Levels



4. Executive Biomechanical Level



a

Fig. 1a. Logical structure of distributed knowledge representation (on information levels) in artificial life of robotic unicycle

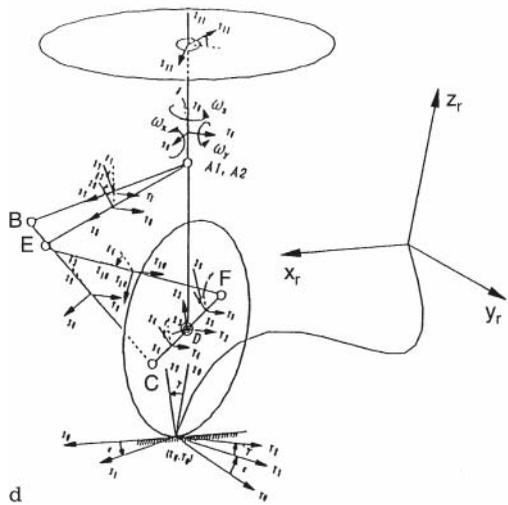
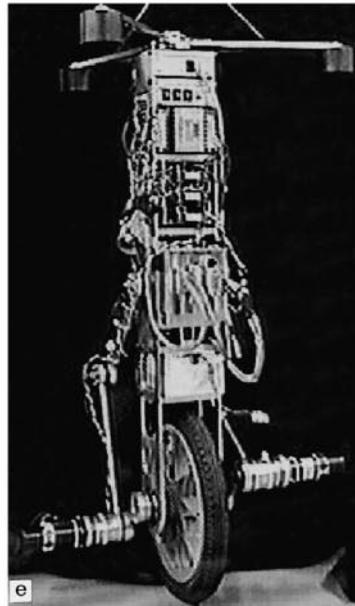
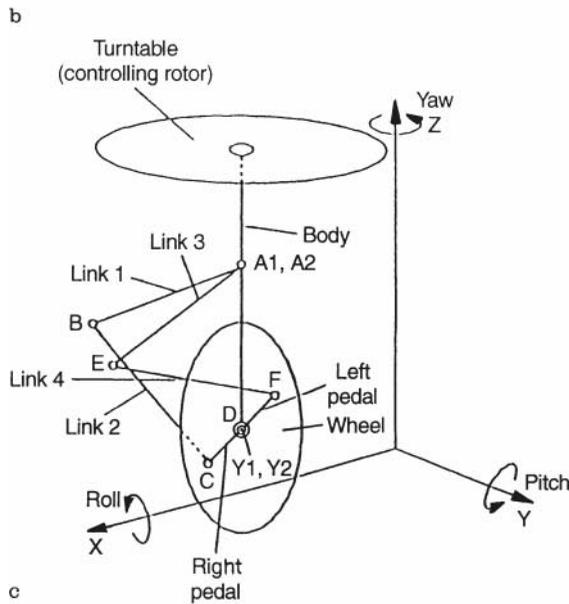
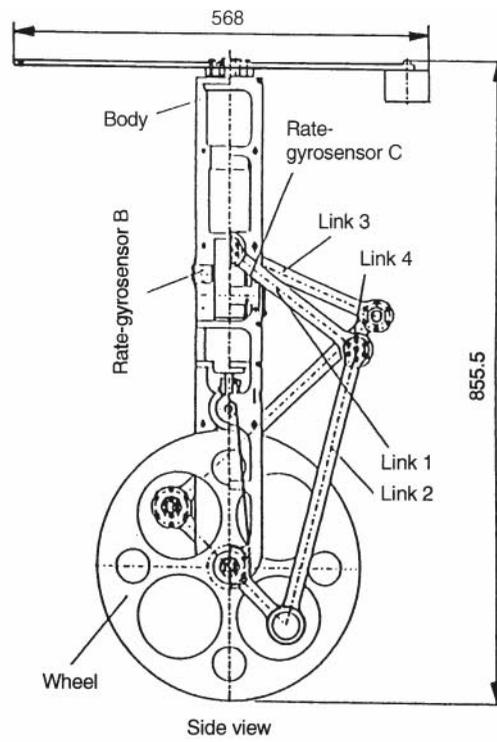
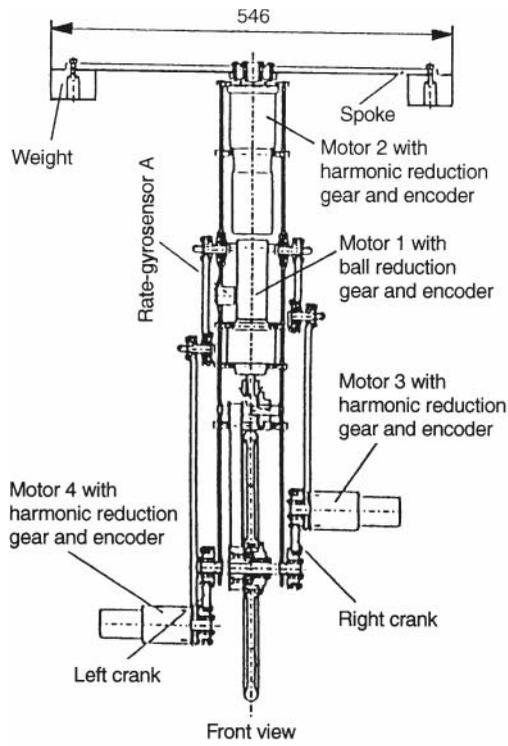


Fig. 1b-e. b Structure of the unicycle robot, c Model for emulating a human riding unicycle by a robot, d Description of coordinates, e Photograph of unicycle robot's stabilized posture in experiment

system are realized as a knowledge base (KB) domain of possible virtual stable states. From qualitative physics description and mathematical simulation of unicycle motion models we obtain the domain of possible virtual stable states described by a strange attractor [38].

At the behavior and coordination level this structure includes *instinct*, *intuition* and *emotion* mechanisms. The instinct mechanism is described in the logic structure as a *local coordinator for the fuzzy rules* and is realized in the control structure as an active and passive adaptation based on FNN. The intuition mechanism represents a global coordinator and is realized in the control process as a random decision-making process on the basis of GA. The emotion mechanism is described on the basis of the sensor information of unicycle motion and is presented in the form of look-up tables with different semantic expressions of linguistic descriptions for the desirable dynamic behavior of the unicycle (for example “fluently”, “fast” and so on). Thus the intersections of two distributed information levels with logical systems, support decision-making systems, and dynamic system models realize the (box of) *artificial brain for the self-organization process* of the robotic unicycle.

The *intelligent control level* is an AI control system with distributed knowledge representation (Fig. 1a) and includes *will* and *mind* mechanisms very similar to a human being. For both, instinct and emotion mechanisms, new look-up tables are introduced on the basis of FNN. Intuition mechanism is realized on the basis of GA and dominates the actions due to the two fuzzy controllers. Mathematical tools based on GA, FNN, and fuzzy simulation for these sub-systems realize soft computing for intelligent smart control.

Executive level is a physical realization process of the biomechanical robotic system. In this case a vestibular system is realized in the robotic unicycle as a logic control system by a balancing turntable, and a neuromuscular system is realized by a closed-link mechanism.

Thus, control of a human riding unicycle with different intelligent levels of behavior can be described as the logic union of intersection levels of a logic system with distributed information levels.

2.2

The robotic model of the unicycle

In the design of a robot model (Fig. 1b) at the executive biomechanical level (Fig. 1a) the rotor is composed of three bars (each of length 285 mm) allocated radially from the rotor’s center. On the tip of each bar a weight (0.9 kg) is fixed symmetrically – a “symmetric rotor”. If we take away one of the weights from the symmetric rotor, it becomes an asymmetric rotor. By the use of the 4-bar closed-link mechanisms (Fig. 1c), the robot’s posture stability in the pitch direction (Fig. 1c and d) can be realized because the acceleration compensation in that direction is attained by the cooperative action of the link mechanisms and the rotor. Thus, the stability in the pitch direction is maintained in spite of changes of the rotor wheel velocity or acceleration (Fig. 1d).

Remark 2 (Related work). Actually, the unicycle problem has attracted some researchers to investigate it. Before our study on the *hardware* unicycle problem, different typical models

were proposed by Ozaka et al. [21], Honma et al. [9] and Schoonwinkel [27]. In Ozaka’s model, the unicycle robot consisted of a wheel, a rigid body and a moveable weight. For that robot, postural stability in the pitch direction was obtained by the control of the wheel, and stability in the roll direction was achieved by the control of the moveable weight that can move in the roll direction. That investigation was conducted in 3D, but the experiment was not successful. A unicycle presented by Honma et al. [9] has a large fast spinning gyroscope at the top of the body, whose posture is stabilized by a controlled precession of the gyroscope. A single-wheel robot was presented by Brown et al. [6]. Their robot has a large tire and the stabilization mechanism is inside the wheel. In Schoonwinkel’s model, the unicycle robot is constructed of three rigid bodies which are the wheel, a frame to represent the unicycle frame and the lower part of the rider’s body and a rotary turntable to present the rider’s twisting torso and arms. Using this model, experiments were conducted by Vos and Flotow [46] and Ito [10] but no successful experimental results in 3D have been reported. In [18] a new mechanism of the robotic unicycle was proposed. One feature of this robot is the shape of the wheel which is similar to a rugby ball. The other feature is that the body is separated into upper and lower parts. Comparing our model with Ozaka and Schoonwinkel’s models, the main difference is in the usage of closed-link mechanism and an asymmetric rotor plays an important role in the unicycle robot’s postural stability control. *Theoretical investigation* and *simulation* of postural stabilization of unicycle models were also studied in [1, 34, 45, 50]. In Takemori’s model a CCD camera and two auxiliary side wheels were used. Stability control was based on H_∞ control theory and on a model reduction method using the weighting functions. Only necessary conditions for robust control on finite time interval are studied. In Usui’s model, two swinging arms to stabilize the rolling motion are used. The equations of motion for a nonholonomic constraint system are linearized and separated into two sub-systems with pitching and rolling motion. The control system is based on the digital optimal theory. Unfortunately, by using linearization techniques for essential nonlinear equations the part of cross braces between pitching and rolling motion vanishes and only necessary conditions of stability can be achieved [43]. The role of nonlinear cross braces in the unicycle model is very important and is used in our model (see below Remark 3). In Yamano’s model Lagrange equations of a unicycle motion are developed and the necessary simple stability conditions without control are describe. In Aicardi’s model Lyapunov techniques are used for closed loop steering of the unicycle. Simplified equations of motion with special choice of system state variables are described and necessary stability conditions for feedback control are introduced. However, we have not found out the real experimental result in 3D about roll angle or roll angular velocity from that paper.

Our study of the rider’s stability control on a unicycle began with the observation and analysis of the logical behaviour of a human riding unicycle due to a vestibular biomechanical model (Fig. 1a). This model described by an intelligent thermodynamic model (qualitative physical representation) including an instinct and intuition mechanisms (as a logical decision-making process). From the observation and model

analysis we found that the rider's thighs and shanks construct a two closed-link loop. This special mechanism plays an important role in the rider's postural stability control in a unicycle system (Fig. 1e). Using this idea we developed a new logic biomechanical model with two closed-link mechanisms and one turntable (rotor) to emulate a human riding unicycle by a robot including an intuition and instinct control of the body behavior based on soft computing. Intuition and instinct mechanisms are considered as global and local search mechanisms for the optimal solution of intelligent behavior and realized on the basis of GA and FNN, respectively. For the fitness function of the GA a new physical measure is the minimum entropy production for the description of intelligent thermodynamic behavior in a biomechanical model and this control system is introduced in [41]. The paper provides a general measure to estimate the mechanical controllability qualitatively and quantitatively even if any control scheme is applied. The measure can be computed (see Appendix A) using a Lyapunov function coupled with thermodynamic entropy change. The interrelation between the Lyapunov function (stability condition) and the entropy production of the motion (controllability condition) in the internal biomechanical model (see Appendix B) is the mathematical background for the design of a soft computing algorithm for the intelligent control of a robot unicycle. Our work deals with the improvement of a fuzzy simulation of the robust intelligent control method with minimum entropy production on the basis of soft computing including GA and FNN.

3 Qualitative physics and thermodynamic equations of motion for the robotic unicycle

Firstly, for the internal world representation of an artificial life for the robotic unicycle we develop now the thermodynamic equations of motion with an asymmetric rotor. The analysis of the robot's postural stability control is carried out and the results are compared with those of our computer simulation. The thermodynamic equations of motion for the robotic unicycle with an asymmetric rotor are given [41] as follows:

$$\begin{bmatrix} \ddot{q} \\ \lambda \end{bmatrix} = \begin{bmatrix} M(q) & -\frac{\partial C}{\partial q} \\ E(q) & 0 \end{bmatrix}^{-1} \times \begin{bmatrix} \tau - B(q)[\dot{q}, \dot{q}] - C(q)[\dot{q}^2] - D(q)[\dot{q}] - G(q) \\ -F(q, \dot{q}) \end{bmatrix}, \quad (1)$$

$$\begin{bmatrix} \frac{dS_u}{dt} \\ \frac{dS_c}{dt} \end{bmatrix} = \begin{bmatrix} M(q) & 0 \\ 1 & 0 \end{bmatrix}^{-1} \times \begin{bmatrix} \tau_d - B(q)[\dot{q}, \dot{q}] - C(q)[\dot{q}^2] - D(q)[\dot{q}] \\ -F(q, \dot{q}) \end{bmatrix} \begin{bmatrix} \dot{q} \\ 0 \end{bmatrix}, \quad (2)$$

where $\tau = (\tau_\psi, 0, 0, 0, 0, \tau_{\theta_1}, 0, \tau_{\theta_2}, \tau_\eta)$, $E(q)$ is a 4×4 coefficient matrix for acceleration, and $F(q, \dot{q})$ is a 4D vector representing Coriolis and centrifugal terms. Both $E(q)$ and $F(q, \dot{q})$ are determined from the constraint equations for a closed-link loop's acceleration; $\partial C/\partial q$ is a 4×4 matrix decided by constraint equations of the two closed-link loops, λ is a 4D

vector of Lagrange multipliers; $M(q)$ is a 9×9 mass matrix; $B(q)$ is a 9×36 matrix of Coriolis coefficients; $[\dot{q}, \dot{q}]$ is a 36×1 vector of velocity products given by $(\dot{q}, \dot{q}) = [\psi \dot{\alpha} \dot{\gamma} \dot{\beta} \dots \dot{\theta}_4 \dot{\eta}]^T$; $C(q)$ is a 9×9 matrix of centrifugal coefficients and $[\dot{q}^2]$ is a 9×1 vector given by $(\dot{q}^2, \dot{\alpha}^2, \dot{\gamma}^2, \dot{\beta}^2, \dot{\theta}_1^2, \dot{\theta}_2^2, \dot{\theta}_3^2, \dot{\theta}_4^2, \dot{\eta}^2)^T$; $D(q)$ is a 9×9 matrix of friction coefficients and $[\dot{q}] = (\dot{\psi}, \dot{\alpha}, \dot{\gamma}, \dot{\beta}, \dot{\theta}_1, \dot{\theta}_2, \dot{\theta}_3, \dot{\theta}_4, \dot{\eta})^T$; $G(q)$ is a 9×1 matrix of gravity terms. The state vector q is defined as $[q] = (\psi, \alpha, \gamma, \beta, \theta_1, \theta_2, \theta_3, \theta_4, \eta)^T$ (see Fig. 1d). In (2) S_u is the entropy of the robot unicycle's motion and S_c is the entropy of both controllers, τ_d are dissipative parts of the control torque (for the PD-controller the dissipative part is described by $k_i(\dot{\gamma}, \dot{\beta})$). The algorithm for the entropy production calculation in the dynamic dissipative systems is described in Appendix A. For the stability analysis and the computer simulation of the robot unicycle's dynamic behavior (1) is written in the traditional form of a different equation as $\dot{q}_i = \varphi_i(q, \tau, t)$.

Remark 3. From (1) we see that there is an essential nonlinearity in the robot unicycle system as cross braces between the phase coordinates. These cross braces have different physical meanings. Our unicycle model has two states: 1) a global dynamic motion in the longitudinal plane; 2) a local kinematic equilibrium with a nonstable zero state in the lateral plane. The nonlinear differential equations of our system contain dissipative and nondissipative nonlinear cross braces, i.e. products of the unicycle motion components in the longitudinal and lateral planes. The nonlinear nondissipative cross braces can be interpreted as parametric disturbances and define Lyapunov stability conditions. The dissipative nonlinear cross braces produce entropy and so they define the controllability of our unicycle model (see Appendix B). A detailed description of the related work about the thermodynamic analysis of differential equations is introduced in [23–25]. From the general stochastic analysis of nondissipative nonlinear cross braces, described in [43, 44] we obtain that, due to parametric disturbances under external sources on the dynamic system, with random initial states in one of the main directions, a diversion from the desired direction seems to appear, with multiple frequencies in the motion of the body. Asymptotic analysis of stochastic stability in [43, 44] indicates that the main frequency range in the lateral plane of unicycle motion is from 0.1–0.2 to 5–10 Hz. The coherence of experimental spectra of this body motion in [12] shows that a galvanic stimulus affects the motion in the frontal plane, whereas much less impact is seen in the sagittal plane. This coherence between a galvanic stimulus and the lateral sway is high also in the frequency range from 0.1–0.2 to 5–10 Hz, although the coherence is low below this frequency range. Here the transfer of vibration energy from one direction to another seems to occur. Small vibrations correspond to a nonstable equilibrium in the lateral plane; it is then compensated by a vibration in the longitudinal plane. So we have a good analogy to describe qualitatively the rider's intelligent behavior on a unicycle.

Results of the analysis indicate that the longitudinal and lateral stability domain is a strange attractor [38]. Both are influenced by each other, so the unicycle system is quite nonlinear with its cross braces. This analysis helps us to understand experimental results of galvanic vestibular

stimulus for the analysis of postural adaptation and stability [12] making the unicycle system much better. It also shows that the improved model is more close to a human riding unicycle as the intelligent robot system.

For the analysis of the robot model stability as an essential nonlinear system we use the asymptotic method of a Lyapunov function and the method of qualitative physics taking advantage of the interrelation between Lyapunov and entropy production functions [25]. A new approach for the definition of the Lyapunov function is also used. The Lyapunov function for the system (1) is defined as $V = \frac{1}{2}(\sum_{i=1}^6 q_i^2 + S^2)$, where $S = S_u - S_c$ and $q_i = (\alpha, \gamma, \beta, \alpha, \gamma, \beta)$. Here we introduce (see Appendix B) the following relation between the Lyapunov function and the entropy production for an *open* system like a unicycle

$$\frac{dV}{dt} = \sum_{i=1}^6 q_i \varphi_i(q_i, \tau, t) + (S_u - S_c) \left(\frac{dS_u}{dt} - \frac{dS_c}{dt} \right). \quad (3)$$

From (3) the necessary and sufficient conditions for the Lyapunov stability of a unicycle are expressed as follows:

$$\sum_{i=1}^6 q_i \varphi_i(q_i, \tau, t) < (S_u - S_c) \left(\frac{dS_c}{dt} - \frac{dS_u}{dt} \right), \quad \frac{dS_c}{dt} > \frac{\partial S_u}{dt}, \quad (4)$$

i.e., a stable motion of a unicycle can be achieved with “negentropy” (following Brillouin’s [5] terminology [23]) S_c and the change of negentropy dS_c/dt in the control system must be subtracted from the change of entropy dS_u/dt , in the motion of a unicycle with the second condition in (4). From (4) the stability measure for the unicycle can be obtained by computing the minimum entropy production of the system and the controllers.

Remark 4. From qualitative physics, an internal world representation of a unicycle has two unstable states: 1) a local unstable equilibrium in the lateral plane (angle of rolling γ); and 2) a global unstable state in the longitudinal plane (angle of pitching β). The two correlation states have to be controlled with two intelligent controllers [37]. This is the necessary and sufficient condition for the improvement of stability control of our unicycle. Approximate reasoning like the fuzzy implication $A \rightarrow B$ realized on FNN, plays the role of a coordinator between look-up tables of two controllers with parallel sequential data processing. This approach differs from the procedural design of the fuzzy hybrid PID-type controllers proposed in [15] for a novel look-up table based self-organizing fuzzy plus linear controller and from [47, 48] for the fuzzy control of a rider–motorcycle system and from [13] for the fuzzy control of electrohydraulic above-knee prostheses. A coordinated action between look-up tables of these two fuzzy controllers is accomplished with GA and FNN. Two fuzzy controllers realize the control of transfer energy with the minimum entropy production from lateral to the longitudinal planes with the help of cross braces in our unicycle model [compensation of transfer energy from the unstable dynamic motion “in large” to the longitudinal plane according to (3)]. The fuzzy controller in the lateral plane executes a role of human riding by organizing a special parametric excitation in the cross braces for the generation of an energy that compensates the transfer energy from the longitudinal plane with the unstable

state (thus, the unstable state “in small” compensates the unstable state “in large”). A stable motion of the unicycle model results from nonlinear control on an intelligent level of correlated energy transfer between two unstable virtual states. Then two adaptive fuzzy controllers realize self-organization of the stability on a unicycle using intuition and instinct schemes. The adaptive method for the feedback gains of fuzzy PD-controllers was realized in [33, 37, 40].

4 Fuzzy intelligent control of a robotic unicycle with soft computing based on GA and FNN

A general approach for the development of a fuzzy controller structure with FNN and GA is described in [11, 19, 26].

In our AI control system (see Fig. 2) two gain schedule PD-controllers are adopted: one is for the asymmetric rotor, and the other for closed link mechanisms. The control torque to the asymmetric rotor is given as

$$\tau_\eta = kp_2 \times k_3 \times \gamma + kd_2 \times k_4 \times \dot{\gamma}; \quad (5)$$

where τ_η is the torque to the rotor, kp_2 and kd_2 are constant feedback gains and k_3 and k_4 are fuzzy schedulers changed in $[0, 1]$ with FNN.

The control torque applied to the links 2 and 4 are given as

$$\tau_{\theta_2} = \tau_{\theta_4} = -kp_1 \times k_1 \times \beta - kd_1 \times k_2 \times \dot{\beta}, \quad (6)$$

where τ_{θ_2} and τ_{θ_4} are the torques to the links 2 and 4, respectively, kp_1 and kd_1 are constant feedback gains, k_1 and k_2 are fuzzy values changed in $[0, 1]$ with FNN.

Remark 5. The biomechanical analysis of posture stability described in [12] shows that PD-control represents the minimum complexity necessary to stabilize posture control. The component P (proportional) contains anti-gravitational forces and compensates the position errors. The component D (derivative) contains an anti-Coriolis compensation and also provides some kind of damping action. The parameters (kp_1, kp_2) may be interpreted as a stiffness (spring constant) arising from passive and active muscular forces, whereas (kd_1, kd_2) might be compared with a viscous damping, as obtained with a wheel dashpot. It suffices to mention that this is the minimum complexity anticipated for a stabilized unicycle model.

The fuzzy tuning rules for k_1, k_2, k_3 and k_4 are formed by the learning system of an FNN (Fig. 3d). Fuzzy controllers are hierarchical, two-level control systems which are intelligent “in small” [51]. The lower (execution) level is the same as a traditional PD-controller and the upper (coordination) level consists of a knowledge base (with a fuzzy inference module in the form of production rules with fuzzy implication) and fuzzification and defuzzification components, respectively. The structure of a fuzzy controller is described in detail in [2, 3, 36, 51].

5 Simulation results

Using the proposed control methods, we performed computer simulations and the control block diagrams are illustrated in Fig. 2. In the first case (see Fig. 3a) GA simulates an intuition

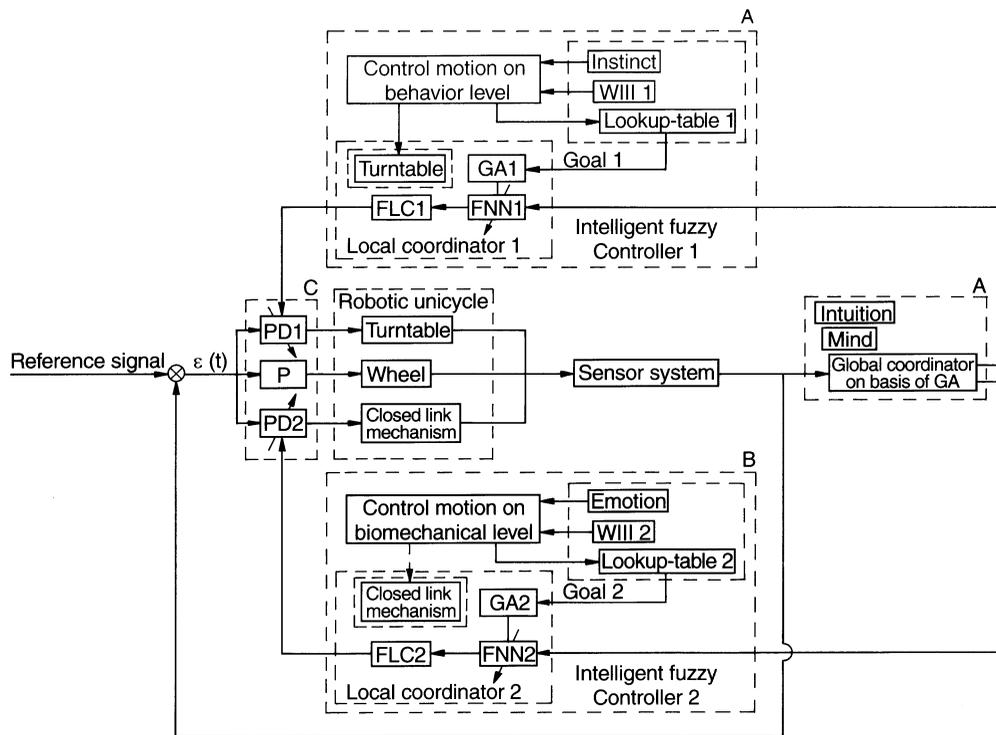


Fig. 2. Structure of the AI control system with distributed knowledge representation (on control signal levels).
A: Intelligence control in “large”, B: Intelligence control in “small”, C: Control on executive level

mechanism of choosing the optimal structure of the PD-controller using the capacity of the fitness function, which is the measure of entropy production and the evolution function, which is in this case entropy.

Structure and parameters of GA. We use a massy GA with elite strategy. Genetic operators have following parameters. For the selection a roulette method (reduce rate=5) is used. A reproduction operator replaces some chromosome generations. Crossover (with probability 0.64) and mutation (with probability 0.08) determines every chromosome bit by random numbers (whether crossover and mutation occur or not). Genes encode each parameter from the interval $[0, 10000]$ and the number of used chromosomes is 100.

Structure of FNN. We use the feed forward structure for FNN with four layers. The FNN is a map of the fuzzy controller structure. We have realized a simple max–min method for the fuzzy inference and the fuzzy production rules. The membership functions are optimized automatically by the back-propagation method. For the simulation, the FNN has 2 inputs, 2 hidden layers (14 units in the first layer and 49 units in the second layer) and 1 output. The main goal of the simulation is to compare the GA and FNN results for the torque and PD-controller parameters with a minimum of entropy production. Figure 3b and c show simulation results of the rotor and link mechanism torque of the optimal PD-controllers with GA. Figures 4a–c and 5a–c show simulation results of entropy production and the entropy of the robot unicycle with PD-controllers. Figures 6a–c show simulation results of entropy production and the entropy in the PD-controller. Figure 7a–c show simulation results of the temporal mechanical and thermodynamic behavior of robot unicycle with

PD-controllers. Figure 3e and f show simulation results of the rotor and link mechanism torque of the FNN-controller. Figure 4d–f and 5d–f show simulation results of the entropy production and the entropy in the robot unicycle with FNN-controllers. Figure 6e–h show simulation results of entropy production and the entropy in the FNN-controller. Figure 7d and e show simulation results of the temporal mechanical and thermodynamic behavior of the robot unicycle with PD and FNN-controllers. For the calculations of the entropy production dS_e/dt (yawing angle), dS_β/dt (pitching angle), dS_γ/dt (rolling angle), we use 452, 201 and 409 dissipative terms, respectively. From the simulation results we obtain that the relation $dS_e/dt > dS_\beta/dt$ from (4) is true and the GA realizes the search of optimal controllers with a simple structure using the principle of minimum entropy production. The FNN controller offers a more flexible structure of controllers with a smaller torque, and the learning process produces less entropy (Fig. 7f and g). FNN controller gives a more flexible structure to controllers with smaller torque and the learning process produces less entropy than GA. Thus, an instinct mechanism produces less entropy than an intuition mechanism. However, the necessary time for achieving an optimal control with the learning process on FNN (instinct) is larger than that with the global search on GA (intuition). The general approach for forming a lookup-table with GA and the fuzzy classifier system based on FNN is described in [20].

6 Fuzzy control of the robot unicycle and physical measure for mechanical controllability

For the fuzzy gain schedule, hybrid PD-controllers proposed in [37] are used for the robot’s postural stability control. The

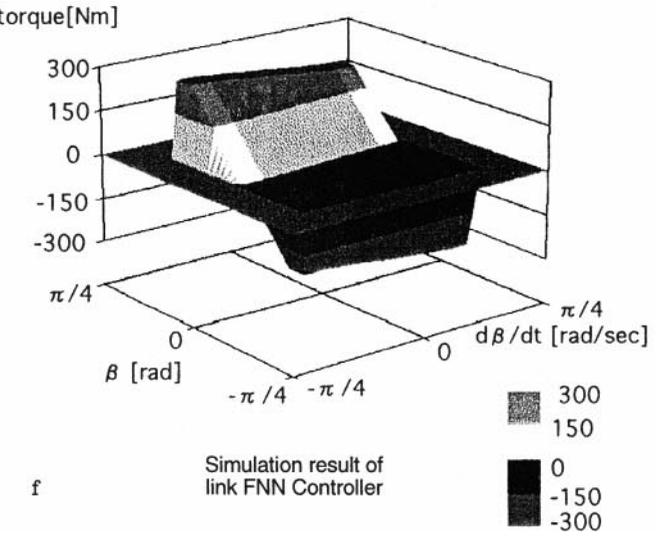
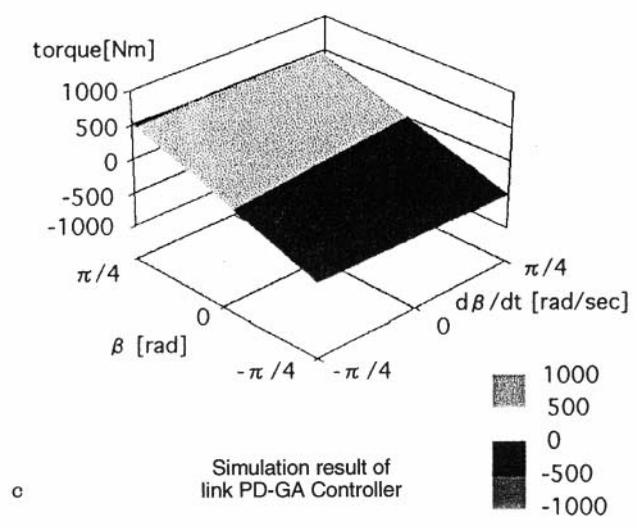
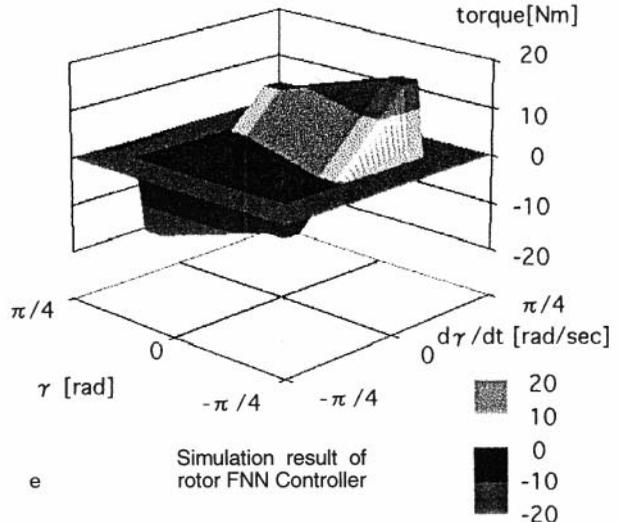
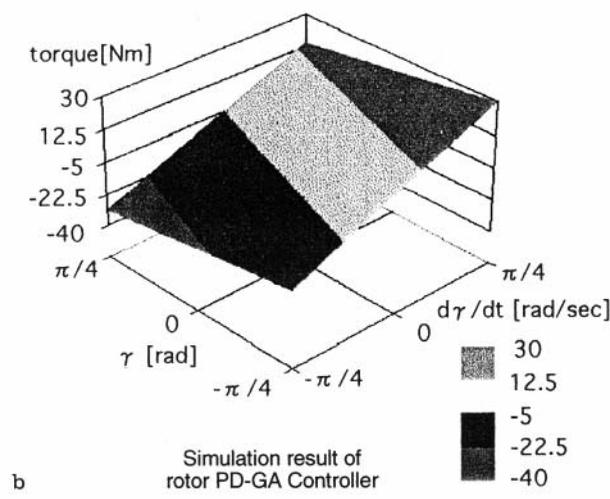
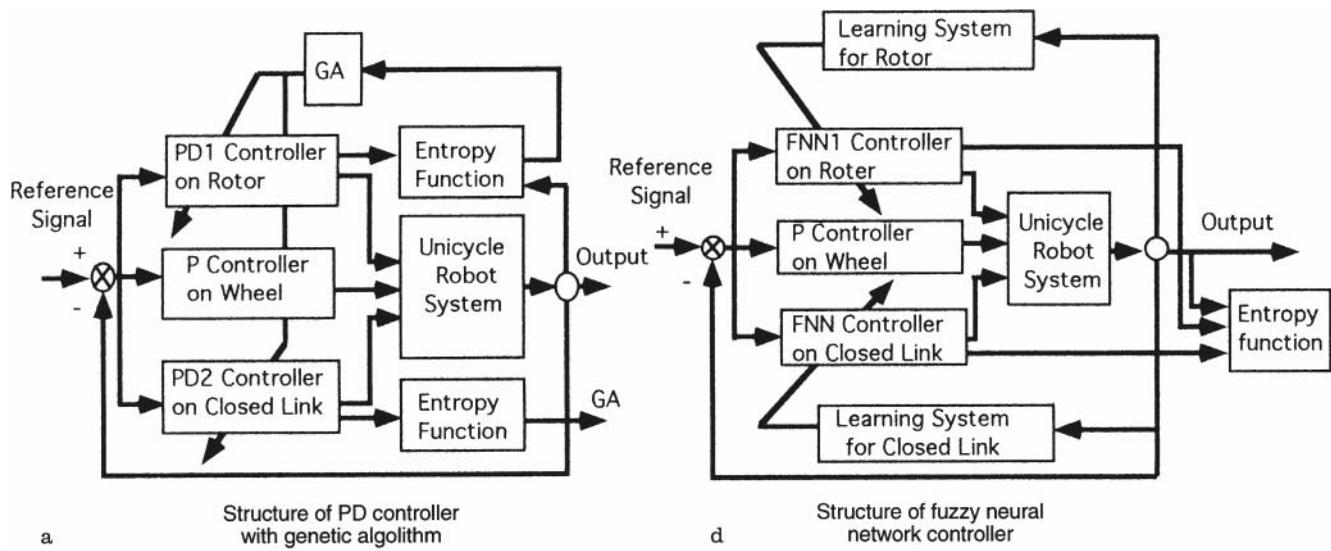


Fig. 3. Structure and simulation results of the unicycle control system with genetic algorithm and fuzzy neural network

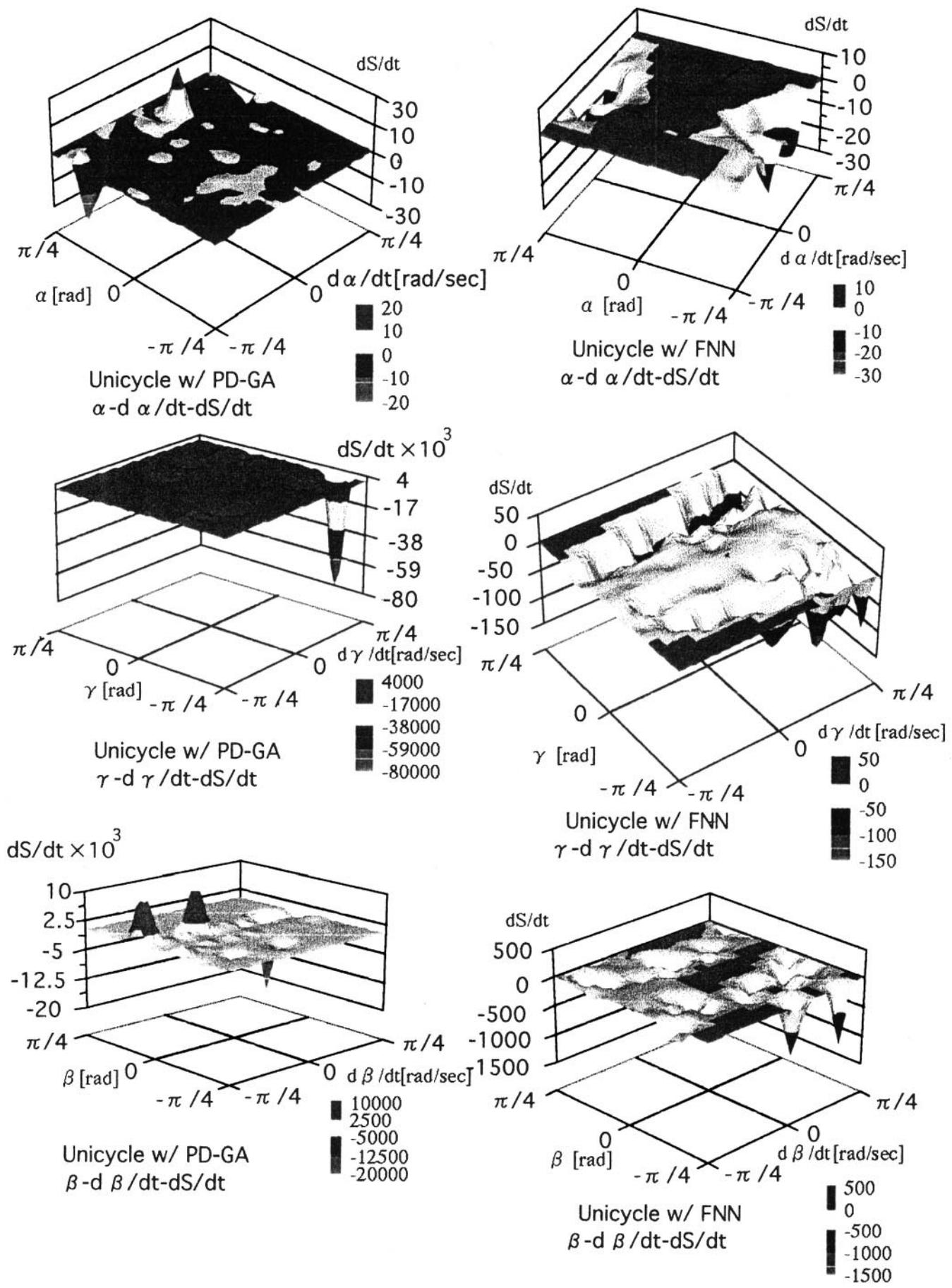


Fig. 4. Simulation results of entropy production in the unicycle control system

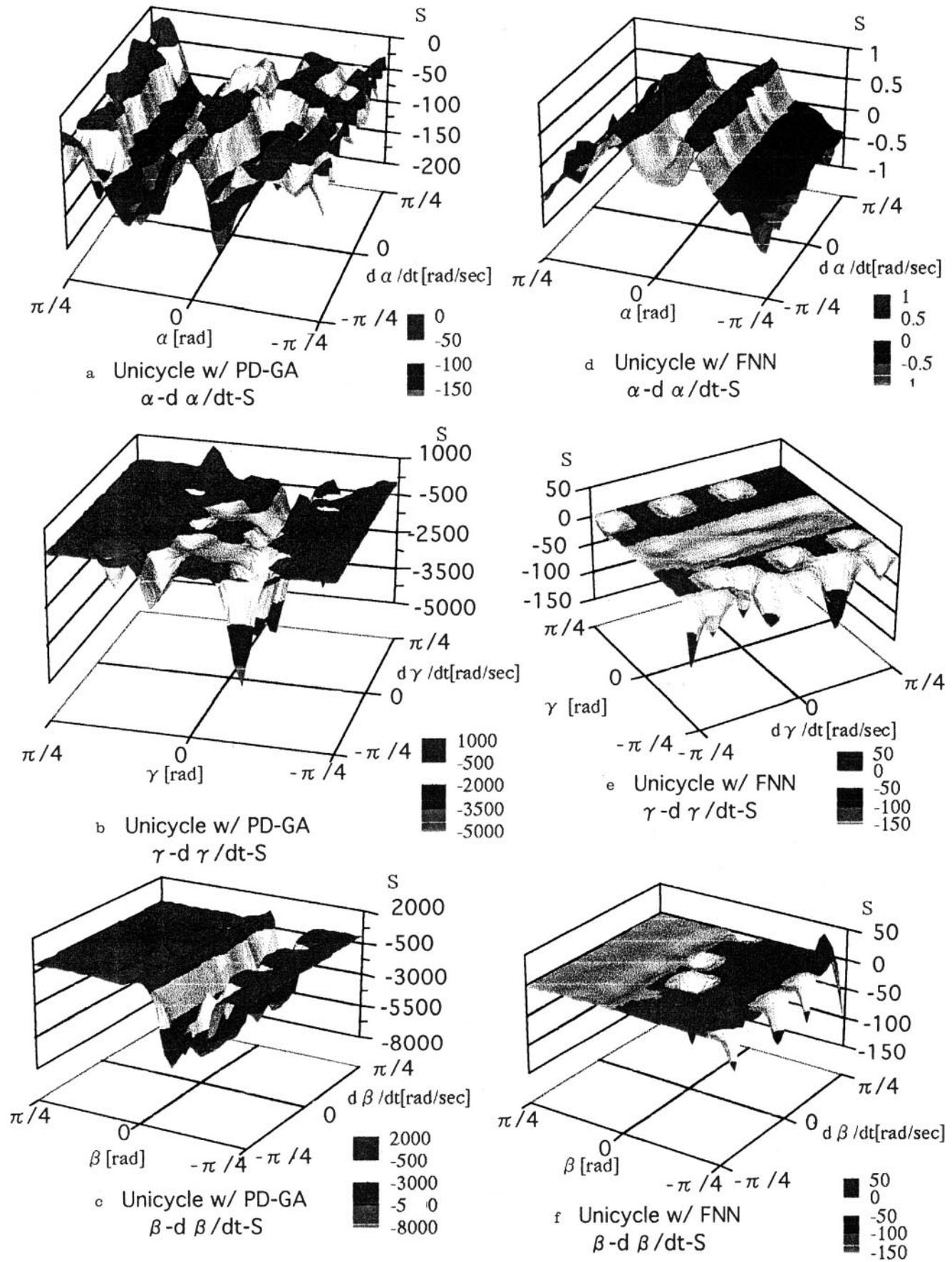


Fig. 5. Simulation results of entropy of the unicycle control system

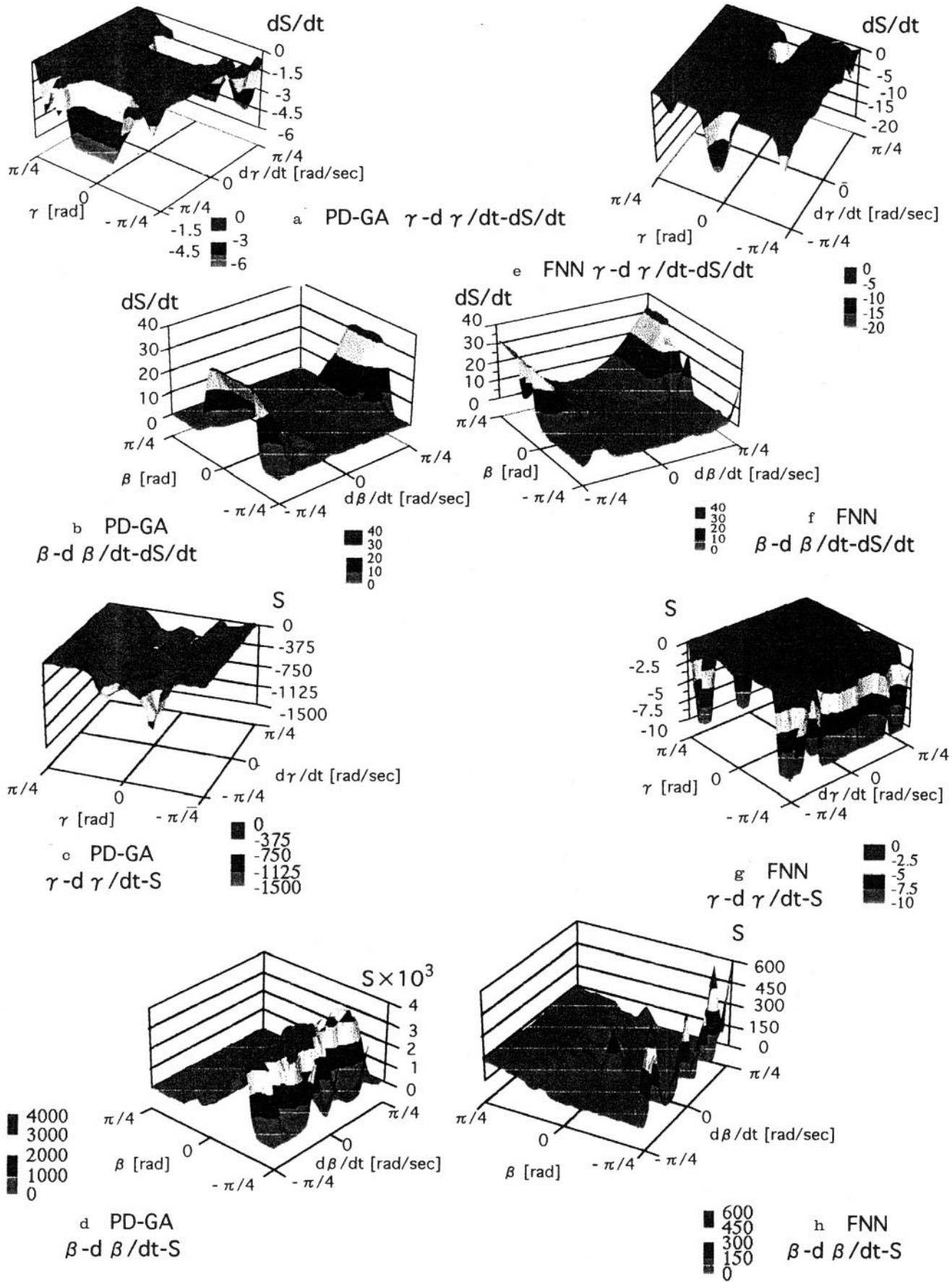


Fig. 6. Simulation results of entropy and entropy production in the PD controller with GA and the fuzzy neural network controller

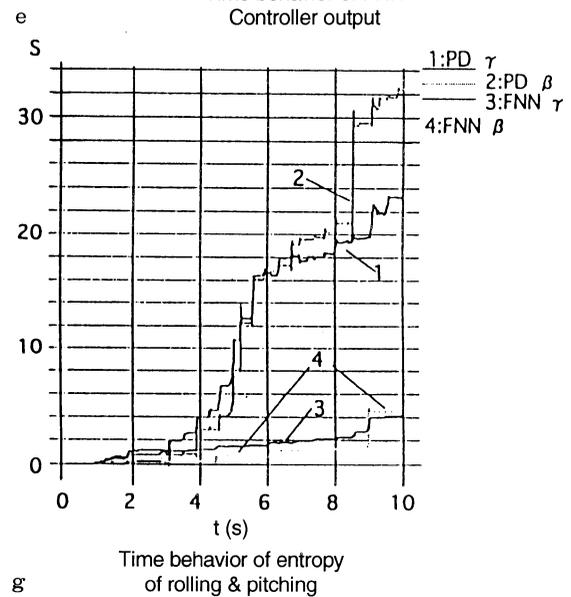
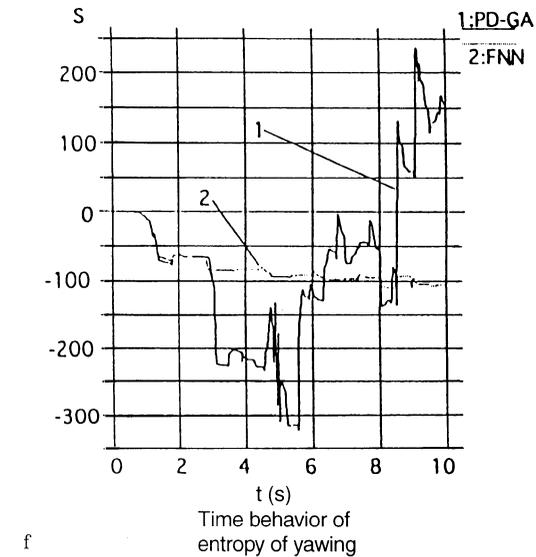
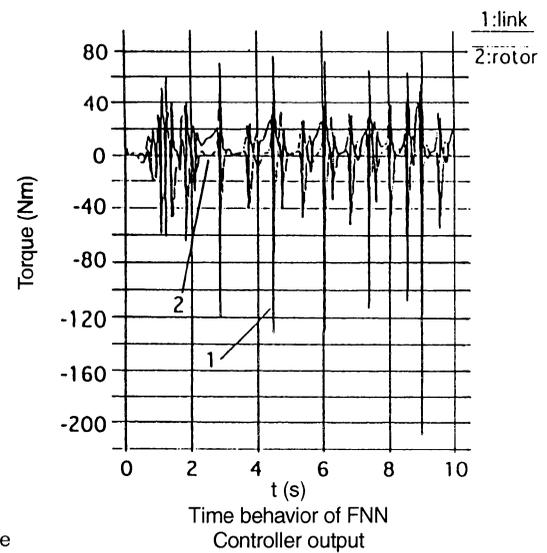
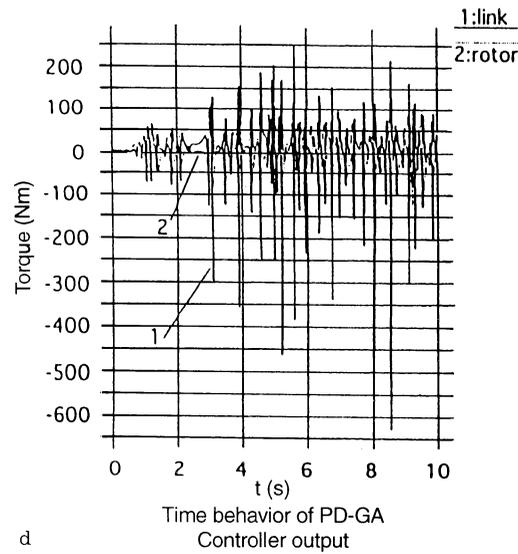
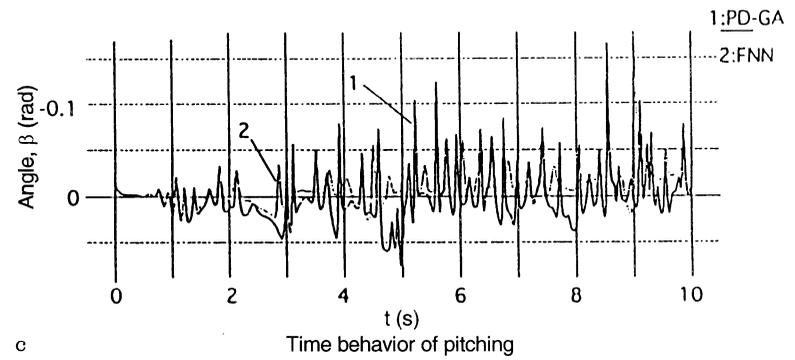
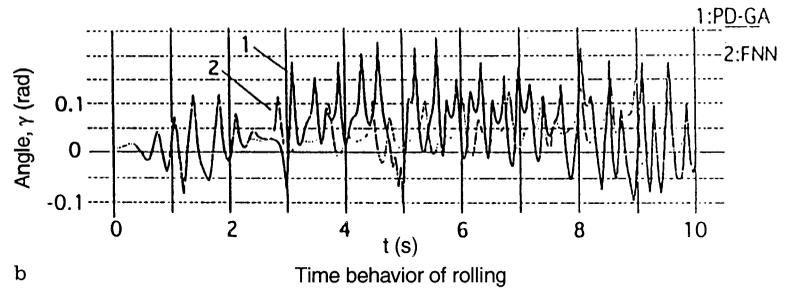
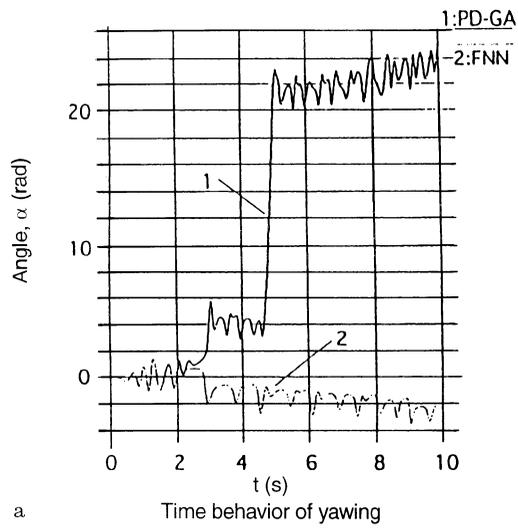


Fig. 7. Simulation results of mechanic and thermodynamic behavior of the robotic unicycle

usage of three rate gyro-sensors installed on the robot for the measurement of the robot's postures in 3D gave us satisfactory results in posture stability and driving. Experimental results [31, 37] show that the robot's longitudinal and lateral postures can both be stabilized successfully. Thus, the proposed fuzzy gain schedule PD-control method provides one of the reasonable approaches to handle such a nonlinear problem existing in the unicycle robot system.

7 Conclusions

In this work, a new fuzzy gain schedule PD control method with look-up tables obtained by FNN and GA using the minimum entropy production as a fitness function is proposed and the obtained simulation results are examined applying three control methods. The following conclusions can be derived:

1. The structures of hardware and software in the AI control system of a robot unicycle for real world applications are developed. The main components of the AI control system based on soft computing and fuzzy control are described.
2. The main idea for a robot unicycle is to change the structure or parameters of two PD controllers with an adaptation method to achieve a stable motion of the unicycle over a long (finite) time interval without changing the structure of the executive level of the control system using soft computing. The background to this approach is the qualitative physical analysis of the unicycle's dynamic motion and the introduction of an intelligence level at the control system by realizing instinct and intuition mechanisms based on FNN and GA accordingly.
3. The introduction of these two new mechanisms to an intelligent control system is based on the principle of minimum entropy production in the robot unicycle's motion and the control system itself. The simulation of thermodynamic equations of motion and the intelligent control system confirm the effectiveness of the robot's postural stability control to handle the system's nonlinearity. In this case the unicycle robot model is a new benchmark for intelligent fuzzy controlled motion of a nonlinear dynamic system with two (local and global) nonstable states.
4. The use of a fuzzy gain schedule PD controller with look-up tables calculated by FNN, offers the ability to use instinct and intuition mechanisms in real time, so that a successful experimental results could be achieved.

Appendix A. Calculation of entropy production for a mechanical system

We cite as an example one benchmark of the entropy production calculation for the Duffing oscillator described as

$$\ddot{x} + \dot{x} - x + x^3 = 0. \quad (\text{A1})$$

From the equation of motion the entropy production [22, 24] is calculated as

$$\frac{dS}{dt} = \dot{x}^2. \quad (\text{A2})$$

The Lyapunov function V for the Duffing equation is described as

$$V = \frac{1}{2} \dot{x}^2 + U(x)$$

where

$$U(x) = \frac{1}{4} x^4 - \frac{1}{2} x^2. \quad (\text{A3})$$

After multiplying the left-hand side of this equation by \dot{x} we get $(\dot{x} + \dot{x} + \partial U(x)/\partial x)\dot{x} = 0$. The value of dV/dt calculated using $dV/dt = \dot{x}\dot{x} + (\partial U/\partial x)\dot{x}$ and after a simple algebraic transformation we obtain

$$\frac{dV}{dt} = -\frac{1}{T} \frac{d_i S}{dt}, \quad (\text{A4})$$

where T is a normalization factor.

This is a generalized relation between the Lyapunov function V (mechanical motion) and the entropy production dS/dt (thermodynamic behavior) instead of as a closed thermodynamic system which is also studied in [8, 14, 28, 35] in another form.

Appendix B. Interrelation between Lyapunov function and entropy production in open dynamic system

Consider the Lyapunov function

$$V = \frac{1}{2} \left(\sum_{i=1}^6 q_i^2 + S^2 \right), \quad (\text{B1})$$

where $S = S_u - S_c$ and $q_i = (\alpha, \gamma, \beta, \dot{\alpha}, \dot{\gamma}, \dot{\beta})$. It is possible to introduce the entropy function S in the Lyapunov function V because entropy S is also a scalar function of time.

Differentiation of the function V with respect to time t gives

$$\frac{dV}{dt} = \sum_{i=1}^6 q_i \dot{q}_i + S \dot{S}. \quad (\text{B2})$$

In this case, $\dot{q}_i = \varphi_i(q_i, \tau, t)$, $S = S_u - S_c$, $\dot{S} = \dot{S}_u - \dot{S}_c$ and we obtain

$$\frac{dV}{dt} = \sum_{i=1}^6 q_i \varphi_i(q_i, \tau, t) + (S_u - S_c) \left(\frac{dS_u}{dt} - \frac{dS_c}{dt} \right), \quad (\text{B3})$$

i.e. (3).

This approach differs from the results in [4, 8, 14].

References

1. Aicardi M, Casalino G, Bicchi A, Balestrino A (1995) Closed loop steering of unicycle-like vehicles via Lyapunov techniques, IEEE Robotics & Automation Magazine, Vol 2, No 1, pp 27–35
2. Aliev R A, Zhakharova E G, Ulyanov S V (1990) Fuzzy control model of dynamic systems (in Russian), Engineering Cybernetics, Vol 29, pp 127–201, VINITI RAS Publ., Moscow
3. Aliev R A, Zhakharova E G, Ulyanov S V (1991) Fuzzy controllers and intelligent industrial control systems (in Russian), Engineering Cybernetics, Vol 32, pp 233–312, VINITI RAS Publ., Moscow
4. Beretta G P (1986) A theorem of Lyapunov stability for dynamical system and a conjecture on property of entropy, J. Math. Phys., Vol 27, No 1, pp 305–308
5. Brillouin L (1959) Information Theory and Science, Academic Press, New York
6. Brown H B, Jr, Xu Y (1996) A single wheel, gyroscopically stabilized robot, Proc. of the 1996 IEEE Int. Conference on Robotics and Automation, Vol 3, pp 3658–3663

7. Feng Q, Yamafuji K (1998) Design and simulation of control system of an inverted pendulum, *Robotica*, Vol 6, No 3, pp 235–241
8. Glansdorff P, Prigogine I (1971) *Thermodynamics of Structure, Stability and Fluctuations*, Wiley-Interscience, New York
9. Honma D, Iguchi N, Kondo Y, Okubo H (1984) One wheel- locomotive robot and its control, *J. of the Robotics Society of Japan*, Vol 2, No 4, pp 366–371
10. Ito S (1994) Study on the Postural Stability and Locomotion Control of an Inverted Pendulum Type Unicycle (in Japanese), Master's Thesis, University of Electro-Communications, Tokyo
11. Jang J-S R, Sun C -T, Mizutani E (1997) *Neuro-Fuzzy and Soft Computing: A computational Approach to Learning and Machine Intelligence*, Englewood Cliffs, NJ: Prentice Hall
12. Johansson R, Magnusson M, Fransson P A (1995) Galvanic vestibular stimulation for analysis of postural adaptation and stability, *IEEE Transactions on Biomedical Engineering*, Vol 42, No 3, pp 282–292
13. Ju M -S, Yi S -G, Tsuei Y -G, Chou Y -L (1995) Fuzzy control of electrohydraulic above-knee prostheses, *JSME International Journal*, Vol 38, No 1, pp 78–85
14. Lavenda B H, Santamato E (1982) Irreversible thermodynamic stability criteria, *Lettere al Nuovo Cimento*, Vol 33, No 17, pp 559–564
15. Lee Y N, Kim T W, Suh I H (1994) A look-up table-based self-organizing fuzzy plus linear controller, *Mechatronics*, Vol 4, No 1, pp 71–90
16. Liu T S, Wu J C (1993) A model for rider-motorcycle system using fuzzy control, *IEEE Transactions on Systems, Man and Cybernetics*, Vol 23-SMC, No 1, pp 267–276
17. Lupina N V, Sleptchenko A N, Ulyanov S V, Shachnazarov M M (1993) Hybrid expert system with deep knowledge representation for diagnostic and design of biotechnological objects, *J. of Computer and Systems Science (Engineering Cybernetics)*, Vol 31, No 3, pp 74–95
18. Nakajima R, Tsubouchi T, Yuta Sh, Koyanagi E (1997) A development of a new mechanism of an autonomous unicycle, *Proc. IROS'97 (IEEE/RSJ Intern. Conference on Intelligent Robots and Systems: Innovative Robotics for Real World Applications)*, Grenoble, France, September 7–11, Vol 2, pp 906–912
19. Nie J, Linkens D A (1995) *Fuzzy-Neural Control, Principles, Algorithms and Applications*, Prentice Hall International (UK) Limited
20. Ohwi J, Ulyanov S V, Yamafuji K (1996) GA in continuous space and fuzzy classifier system for opening a door with manipulator of mobile robot: New Benchmark of evolutionary intelligent computing, *J of Robotics and Mechatronics*, Vol 8, No 3, pp 297–301
21. Ozaka C, Kano H, Masubuchi M (1981) Stability of a monocycle-type inverted pendulum (in Japanese), 3rd Vehicle Automation Symp. of Japan Automation Control Society, pp 63–66; (1980), *Stabilization of unicycle, System and Control*, Vol 25, No 3, pp 159–166
22. Perround M, Saucier A (1987) *Thermodynamics of dissipative systems*, *Helvetica Physica*, Vol 60, No 8, pp 1038–1051
23. Petrov B N, Ulanov G M, Ulyanov S V, Khazen E M (1977) *Informational and Semantic Problems in Control Processes and Organization (in Russian)*, Nauka Publ., Moscow
24. Petrov B N, Goldenblat I I, Ulyanov S V (1978) *Model Theory of Control Processes: Information and Thermodynamic Approach (in Russian)*, Nauka Publ., Moscow
25. Petrov B N, Ulanov G M, Ulyanov S V (1979) *Dynamic systems with random and fuzzy structures (in Russian)*, *Engineering Cybernetics*, Vol 11, pp 3–76, VINITI RAS Publ., Moscow
26. van Rooij A J F, Jain L C, Johnson R P (1997) *Neural Network Training Using Genetic Algorithms (Machine Perception and Artificial Intelligence)*, Vol 26), World Scientific Pub., SGP
27. Schoonwinkel A (1987) *Design and Test of a Computer Stabilized Unicycle*, Ph.D. thesis, Stanford University, USA
28. Sertorio L (1985) Remarks on the excess availability dissipation, *IL Nuovo Cimento*, Vol 90B, No 2, pp 127–136
29. Sheng Z Q, Yamafuji K (1994) A general method for the direct dynamic computation of closed link mechanisms, *Journal of Robotics & Mechat.*, Vol 6, No 2, pp 169–174
30. Sheng Z Q, Yamafuji K (1995a) Realization of a human riding a unicycle by a robot, *Proc. of '95 IEEE Intern. Conf. on Robotics & Automation*, Japan, Vol 2, pp 1319–1326; (1997) Postural stability of a human riding a unicycle and its emulation by a robot, *IEEE Trans. on Robotics and Automation*, Vol 13, No 5, pp 709–720
31. Sheng Z Q, Yamafuji K (1995b) Study on the stability and motion control of a unicycle, 1st Report: Dynamics of a human riding a unicycle and its modeling by link mechanism, *JSME International Journal*, Vol 38C, No 2, pp 249–259
32. Sheng Z Q, Yamafuji K (1995c) Study on the stability and motion control of a unicycle, 2nd Report: Design of unicycle robot and experimental results (in Japanese), *Trans. of Japan Soc. of Mech. Engineers (JSME)*, Vol 61C, No 583, pp 306–313
33. Sheng Z Q, Yamafuji K, Ulyanov S V (1996) Study on the stability and motion control of a unicycle. Pts 3, 4, 5, *JSME International Journal*, Vol 39, No 3, pp 560–568, 569–576; (1996b) *Journal of Robotics & Mechatronics*, Vol 8, No 6, pp 571–579
34. Takemori F, Miyashita T, Okuyama Y (1995) Stabilization control of a mono-cycle by reduction method using weighting functions (in Japanese), *ROBOMECH'95*, Yamaguchi-Ube, Japan, No 95-17, pp 503–504
35. Tasso H (1993) Lyapunov stability of large systems of van der Pol-like oscillators and connection with turbulence and fluctuation spectra, *Physics Letters*, Vol 183A, No 2, 3, pp 165–168
36. Ulyanov S V (1992) Fuzzy models of Intelligent control systems: Theoretical and applied aspects *Soviet Journal of Computer and Systems Sciences (Engineering Cybernetics)*, Vol 30, No 4, pp 1–22
37. Ulyanov S V, Sheng Z Q, Yamafuji K (1995a) Fuzzy Intelligent control of robotic unicycle: A New benchmark in nonlinear mechanics, *Intern. Conf. on Recent Advanced Mechatronics*, Istanbul, Turkey, Vol 2, pp 704–709
38. Ulyanov S V, Sheng Z Q, Yamafuji K, Watanabe S, Ohkura T (1995b) Self-organization fuzzy chaos Intelligent controller for a robotic unicycle: A new benchmark in AI control, *Proc. of 5th Intelligent System Symposium: Fuzzy, AI and Neural Network Applications Technologies (FAN Symp, '95)*, Tokyo, pp 41–46
39. Ulyanov S V, Yamafuji K, Fukuda T, Arai F, Rizzotto G G, Pagni A (1995c) Quantum and thermodynamic self-organization conditions for artificial life of biological mobile nano-robot with AI control: Report I. Quantum motion and thermodynamic stability, *Proc. of IEEE Forum on Micromachine and Micromechatronics*, Nagoya, Japan, pp 15–24
40. Ulyanov S V, Yamafuji K (1996a) Fuzzy Intelligent emotion and instinct control of a robotic unicycle, 4th Intern. Workshop on Advanced Motion Control, Mie, Japan, Vol 1, pp 127–132
41. Ulyanov S V, Watanabe S, Yamafuji K, Ohkura T (1996b) A new physical measure for mechanical controllability and intelligent control of a robotic unicycle on basis of intuition, instinct and emotion computing, 2nd Intern. Conf. on Application of Fuzzy Systems and Soft Computing (ICAF'96), Siegen, Germany, pp 49–58
42. Ulyanov S V, Yamafuji K, Fukuda T, Arai F, Rizzotto G G, Pagni A (1996c) Quantum and thermodynamic self-organization conditions for artificial life of biological mobile nano-robot with AI control: Report 2. Methodology of R&D and stochastic dynamic, *Proc. of 7th Intern. Symposium on Micro Machine and Human Science*, Nagoya, Japan, pp 241–248
43. Ulyanov S V, Feng Q, Yamafuji K, Ulyanov V S (1998a) Stochastic analysis of nonlinear dynamic system with time-variant structure, Pts 1, 2, *Probabilistic Engineering Mechanics (published)*
44. Ulyanov S V, Yamafuji K, Ulyanov V S, Fukuda T, Arai F, Kurawaki I (1998b) Interrelation between entropy production and Lyapunov stability of relaxation processes in nonlinear closed dissipative dynamic system, *Physics Letters A (accepted)*
45. Usui S, Kamoshita S, Nagata Y (1996) Postural stabilization of a unicycle (in Japanese), *Trans. Japan Soc. Mech. Engineers (JSME)*, Vol 62, No 600, pp 184–191

46. Vos D W, von Flotow A H (1990) Dynamics and nonlinear adaptive control of an autonomous unicycle: Theory and experiment, Proc. of 29th Conf. on Decision and Control, Honolulu, Hawaii, pp 128–187
47. Wu J C, Liu T S (1995) Fuzzy control of rider-motorcycle system using genetic algorithm and auto-tuning, Mechatronics, Vol 4, No 4, pp 441–455
48. Wu J C, Liu T S (1996) Fuzzy control stabilization with application to motorcycle control, IEEE Transactions on Systems, Man and Cybernetics, Vol 26, No 6, pp 836–847
49. Yamafuji K, Inoe K (1986) Study on the postural stability of a unicycle (in Japanese), JSME/JSPE Symp. in Yamanashi, Japan, pp 4–6
50. Yamano K, Abe N, Kanoh H (1994) Stability analysis of mono-cycle (in Japanese), 12th Conference of Robotic Society of Japan, Vol 3, pp 1195–1196
51. Zhakharov V N, Ulyanov S V (1995) Fuzzy models of intelligent industrial controllers and control systems. Pts 2, 3, Journal of Computer and Systems Sciences International, Vol 33, No 2, pp 94–108; 117–136