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Paper:

Computational Intelligence with New Physical Controllability Measure for Robust Control Algorithm of Extension-Cableless Robotic Unicycle

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The biomechanical robotic unicycle system uses internal world representation described by emotion, instinct, and intuition. The basic intelligent control concept for a complex nonlinear nonholonomic biomechanical systems, as benchmark the *extension-cableless robotic unicycle*, uses a *thermodynamic approach* to study optimum control processes in complex nonlinear dynamic systems is represented here. An algorithm for calculating the entropy production rate is developed. A new physical measure, the minimum entropy production rate, is used as a Genetic Algorithm (GA) fitness function to calculate robotic unicycle robustness controllability and intelligent behavior. The interrelation between the Lyapunov function – a measure of stochastic stability – and the entropy production rate – the physical measure of controllability – in the biomechanical model is the mathematical background for designing soft computing algorithms in intelligent robotic unicycle control. The principle of minimum entropy production rate in control systems and control object motion in general is a new physical concept of smart robust control for the complex nonlinear nonholonomic biomechanical system, as benchmark, *extension-cableless robotic unicycle.*

Keywords: Autonomous extension-cableless robotic unicycle, Soft computing algorithms, Robust Intelligent control, Posture stability, Controllability

1. Introduction

This article introduces flexible design of soft computing algorithms for intelligent robust control of advanced robotics as an *extension-cableless robotic unicycle* (**Fig.1**). As *benchmarks* of advanced computational intelligence, we discuss in detail soft computing algorithm applications based on a new fuzzy simulation structure, fuzzy neural network (FNN), and GA to intelligent control of *extension-cableless robotic unicycles* (control objects, Fig.1). The artificial *extension-cableless robotic unicycle* life (**Fig.2**) is described using *internal* world representation.[9]

Intelligent mechatronics is based on results of new nonlinear mechanical system motion, modern control, and intelligent computation in developing smart control algorithms. The extraction of knowledge from new movement is based on benchmarks. Unicycle motion is described as nonlinear nonholonomic, global unstable, and dynamic system. Related research on dynamic systems is interesting for nonlinear mechanics to develop new nonlinear effects research and for modern control theory to develop new intelligent control algorithms.

The development of a benchmark algorithm and control system, such as an robotic unicycle, requires a new calculation – computational intelligence.

The physical feature of benchmarks is that unicycle control is realized by a skillful human operator. The unicycle is studied as a biomechanical system including new phenomena in control such as intuition, instinct, and emotion. It is an algorithmically unsolvable problem for advanced control system theory based on conventional calculation. Control of unicycle movement is based on logical coordination of complex movement components (pedaling and movement of the operator's trunk). Change in coordination types sets up new movements – straightforward movement, obstacles avoidance, dancing, and jumping. The unicycle is a good example of a simulator for rehabilitation and training in the use of artificial limbs.

The control of nonlinear global unstable objects such as the unicycle requires new control system. We introduce a new physical control principle: *the minimum entropy production rate in control systems and in control object motion in general.* The physical measure of entropy production rate is a GA fitness function. Such an approach ensures the global dynamic stability of the control object and provides *robust control.* Based on this approach, we developed *self-organized AI robust control system design with a physical measure of control quality* with new intelligence feedback (**Fig.3**). Innovative intelligence feedback is based on intelligent computation principles. In off-line mode based on a developed algorithm, entropy production is calculated in movement and control. Based on the entered fitness function, GA selects an optimum solution from all possible solutions as laws of change for PD controller parameters. The developed control law is an FNN teaching signals used in training and adaptation to the control law. The FNN output

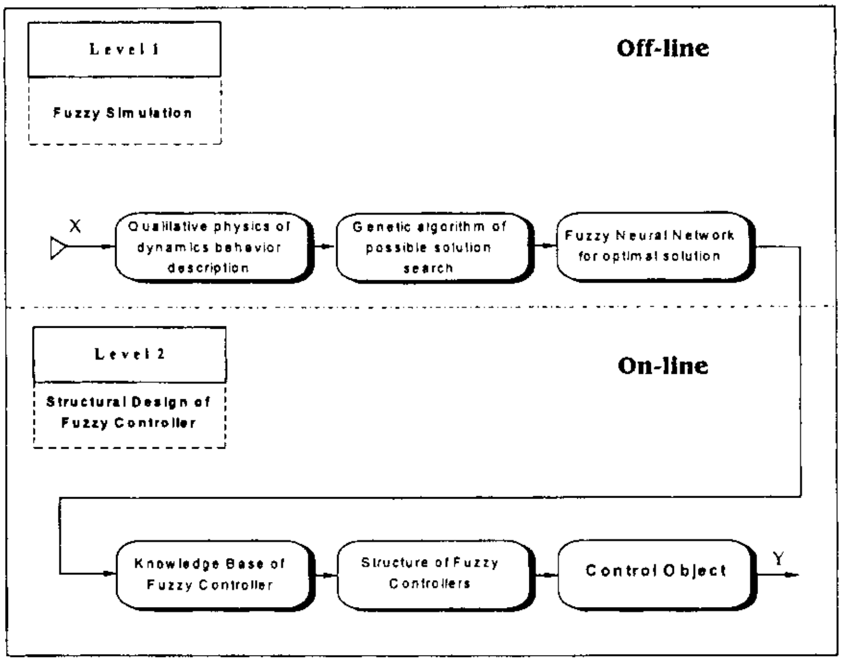


Fig. 1. Fuzzy Simulation Structure with Soft Computing and Intelligent Controller Design

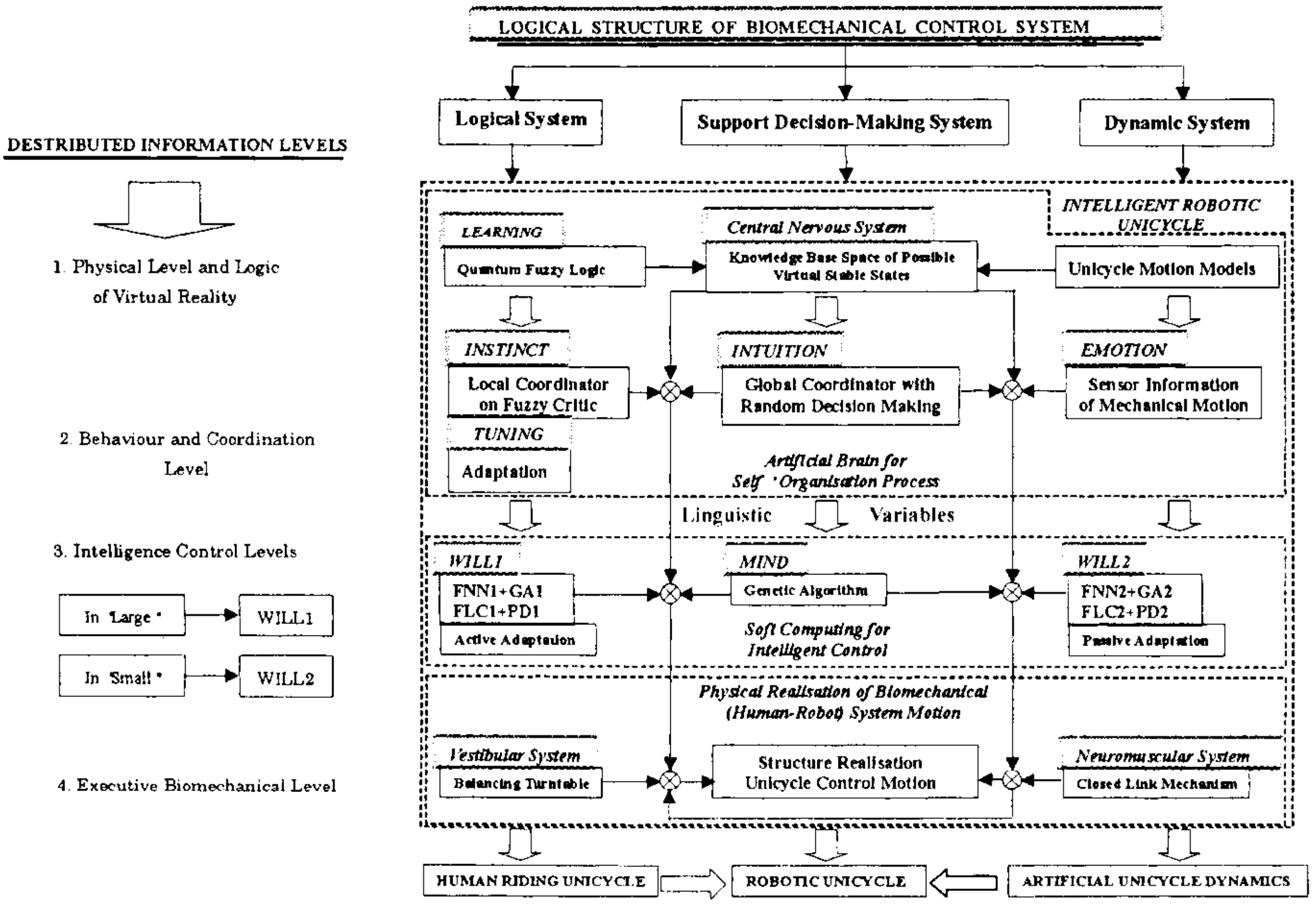
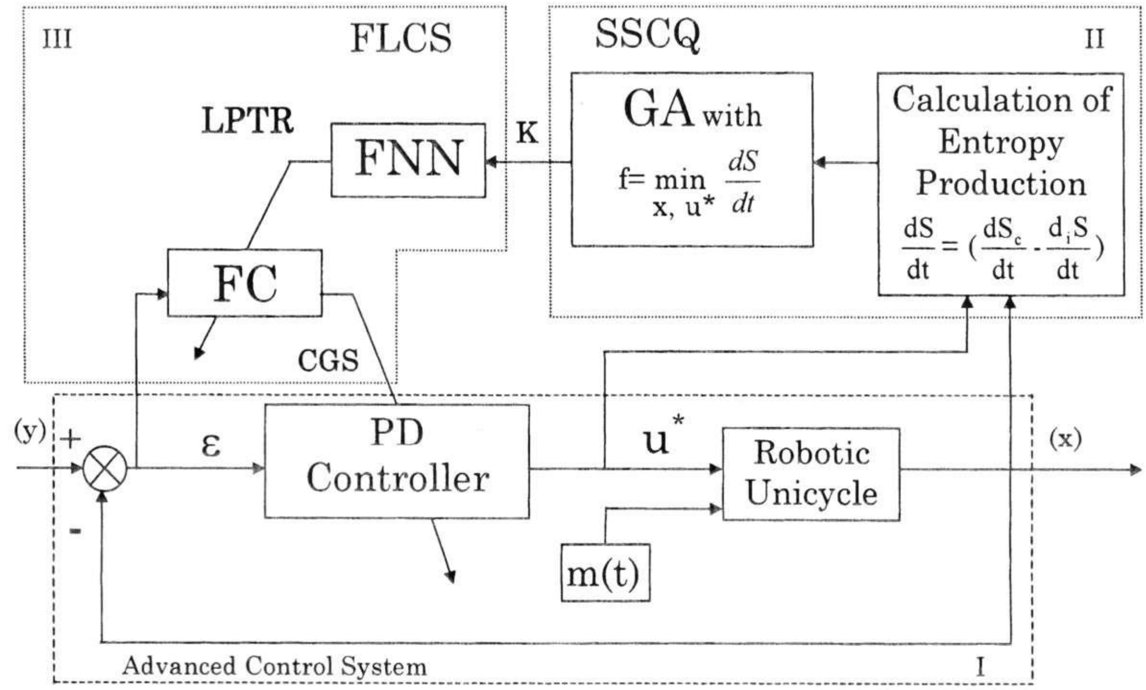


Fig. 2. Conceptual Logical Structure of Distributed Knowledge Representation (on Information Levels) in Artificial Life of Extension-Cableless Robotic Unicycle

signal forms the Fuzzy Controller (FC) lookup table. Lookup tables, change the PD controller parameters.

Earlier similar unicycles were considered only from a mechanical model with application of the advanced control method (ACM) or a simplified hybrid fuzzy PD controller (FPD) (early robotic unicycle). This does not provide global dynamic stability to control objects and robustness control system. The ACM and intelligent control must be applied based on studying of skilled operator (**Fig.4**).

A unicycle is only a mechanically unstable model with-



Designations:

1. GA - Genetic Algorithm;
2. f - Fitness Function of GA;
3. S- Entropy of System;
4. S_c - Entropy of Controller;
5. S_i - Entropy of Controlled Plant;
6. ε - Error;
7. u*- Optimal Control Signal;
8. m(t) - Disturbance;
9. FC - Fuzzy Controller;
10. FNN - Fuzzy Neural Network;
11. FLCS - Fuzzy Logic Classifier System;
12. SSCQ - Simulation System of Control Quality;
13. K - Global Optimum Solution of Coefficient Gain Schedule (Teaching Signal);
14. LPTR - Look-up Table of Fuzzy Rules;
15. CGS - Coefficient Gain Schedule $K=(k_1,k_2,k_3,k_4)$.

Fig. 3. Self-Organization of AI Robust Control System Design with Physical Measure of Control Quality

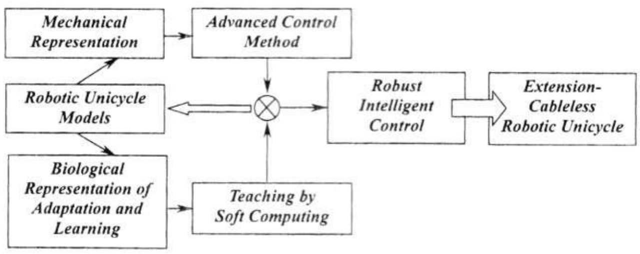


Fig. 4. Research and Development Concept

out an operator; without skill and adaptive intelligence control, the model remain uncontrolled and unstable. The basic research concept is studying of a nonlinear biomechanical *extension-cableless robotic unicycle* model taught based on accessible soft computing tools to create robust intelligence control system, as detailed below.

Remark 1. A new physical measure, the *minimum entropy production rate* for describing intelligent dynamic behavior and thermodynamic stability condition[6,7,10] of a biomechanical model with AI control for the robotic unicycle are introduced. This physical measure is used as a GA fitness function for computer simulation of the intuition mechanism as a *global* random search for decision-making about optimum control of global stability in the robotic unicycle throughout the full space of possible solutions. Instinct mechanism simulation based on FNN is *local* active adaptation process with the minimum entropy production rate in learning by the vestibular system teaching control signals to model representation results.[7] Unlike in some papers,[4,5] our computer simulation uses *thermodynamic* equations for motion[7,10] of the robotic unicycle. Entropy production rate and entropy measures for robotic unicycle motion and control are calculated directly from thermodynamic equations of motion.

From fuzzy simulation and soft computing results based on GA and FNN, intelligent behavior controllability and postural stability of a robot is improved by 2 fuzzy gain schedule PD controllers over that controlled only by a conventional PD and a fuzzy gain schedule PD controller.[5] We confirmed that the proposed fuzzy gain schedule PD-controller effectively handles system nonlinearity in robot posture stability control. The principle of minimum entropy production rate quantitatively measures controllability and qualitative explanations. Our *new benchmark* controls unstable essentially nonlinear nonholonomic dynamic systems by intelligent tools[4,6,7,9] based on a new physical robust control concept (**Fig.5**).

We developed AI control hardware and software for the extension-cableless robotic unicycle in real world applications, describing its main components based on soft computing and fuzzy control. For the robotic unicycle, we use soft computing to change structures or parameters of 2 PD controllers with adaptation and achieve stability motion of unicycle over long (finite) time intervals without changing the executive level of control. The background to this ap-

Fig. 5. Relationship between Stability, Robustness, and Controllability

proach is qualitative physical analysis of unicycle dynamic motion and the introduction of intelligent control realizing instinct and intuition based on FNN and GA.

2. Biomechanical Qualitative Control Model with Extension-Cableless Robotic Unicycle Model

A human rider controls a unicycle using torso, shoulders, and arms quite complicatedly and not always symmetric to the wheel's principal axis. The improved unicycle model[5] involves 2 unique, characteristic structures – an overhead rotor on the torso (body) and a double 4-bar closed link on both sides of the wheel – playing important roles in biomechanical control.

2.1. Biomechanical Control Model.

Human riding control of a unicycle as a logic-dynamic hierarchy consists of: 1) a dynamic mechanical human riding unicycle; 2) unicycle intelligent control decision making process with different levels of *skill* operations; 3) logic behavior for coordination of the torso and feet based on *intuition, instinct, and emotion*; and 4) distributed information system for cooperatively coordinating biomechanical model subsystems.[7] Based on this dynamic control representation, we use a conceptual hierarchical logic structure of distributed knowledge representation for artificial robotic unicycle life (Fig.2). To describe this life, we use qualitative physics for internal world representation based on a mathematical unicycle motion model.

Logic structure of biomechanical control for describing a human riding unicycle include 4 levels: 1) distributed information with sublevels; 2) logic; 3) support decision making; and 4) dynamic mechanics.

Distributed information includes 4 sublevels: 1) physical and logic of virtual reality; 2) behavior and coordination; 3) intelligent control with 2 sublevels; and 4) executive biomechanical. Intersections between horizontal lines of distributed information levels and vertical lines of *logic*, *support decision making*, and *dynamics* of unicycle motion, and a *human behavior* as biomechanical control model provide models for human riding unicycles with different skill in smart control tools.

Consider some examples:

Example 1: *Physical and logic levels of virtual reality.* An intersection of the first horizontal and first vertical levels (logic) give as a result learning the structure of human riding unicycle control; an intersection with the second vertical level (support decision making) corresponds to the level of the central nervous system (CNS) as biological control; and an intersection with the third level (dynamic mechanical) introduces mechanical models of unicycle motion as dynamic system. The logic sum of these sublevels gives the physical level of unicycle motion description and physical interpretation of data observation and measurement. The mathematical background for describing learning is *quantum fuzzy logic*. CNS functions are realized as a knowledge base domain of possible virtual stable states. To make control at so high an intelligent level is not currently possible.

Example 2: On *behavior and coordination levels,* this structure include *instinct*, *intuition* and *emotion*. Instinct is described in the logical structure as a *local coordinator* of fuzzy critic rules and corresponds in control to *active* and *passive* adaptation based on FNN. Intuition is represented as a global coordinator and realized in control as random decision making process based on GA. Emotion is described based on sensor information of unicycle motion and presented as lookup tables with different semantic expressions of linguistic describing desirable dynamic unicycle motion, e.g., fluently and fast. The intersections of 2 distributed information levels with logical systems, support decision making, and dynamic system models realize the *artificial brain for self-organization* of the robotic unicycle.

Example 3: *Intelligent control level* is AI control with distributed knowledge representation[8,10] and includes *will* and *mind*. For both instinct and emotion, new lookup tables are introduced based on FNN. *Intuition* is realized based on GA and dominates action due to the 2 fuzzy controllers. Mathematical tools are based on GA and FNN. Fuzzy simulation for subsystems realizes soft computing for intelligent smart control.

From qualitative physics and mathematical simulation of unicycle motion models, we obtain the domain of possible virtual stable states described by a strange attractor.[5,6] This agrees with the fact[3] that human postural control is highly complex and the human body sways stochastically.

Example 4: *Executive level* is physical realization of a biomechanical robotic system – a vestibular logical control realized in the robotic unicycle by a balancing turntable. The neuromuscular system is realized by a closed link mechanisms. Thus, control of a human riding unicycle with different intelligent levels of behavior is described as a logical union of intersection levels of logical systems with distributed information levels.

Remark 2. Human postural control involves multiple sensory and motor components. As a biological model, we chose the vestibulocerebellum and spinocerebellum including the vermis and intermediate zones of hemispheres. The vermis is related to axial motor control and intermediate zones to distal motor control. The vermis and intermediate zones are based on feedback error learning for closed-loop control (Fig.2). The cerebellum provides adaptive feedback control and learns how to execute coordinative and predictive control of complicated controlled objects such as the trunk and limbs.[1] This adaptive feedback control is overlaid onto more basic feedback in the spinal cord, brain stem, and cerebral cortex. Thus, 2 feedback controllers cooperate to execute robotic unicycle movement. Two compelling reasons exist for regarding the vestibulocerebellum and spinocerebellum as adaptive feedback controllers. First, unlike the lateral cerebellum, it receives information directly from the

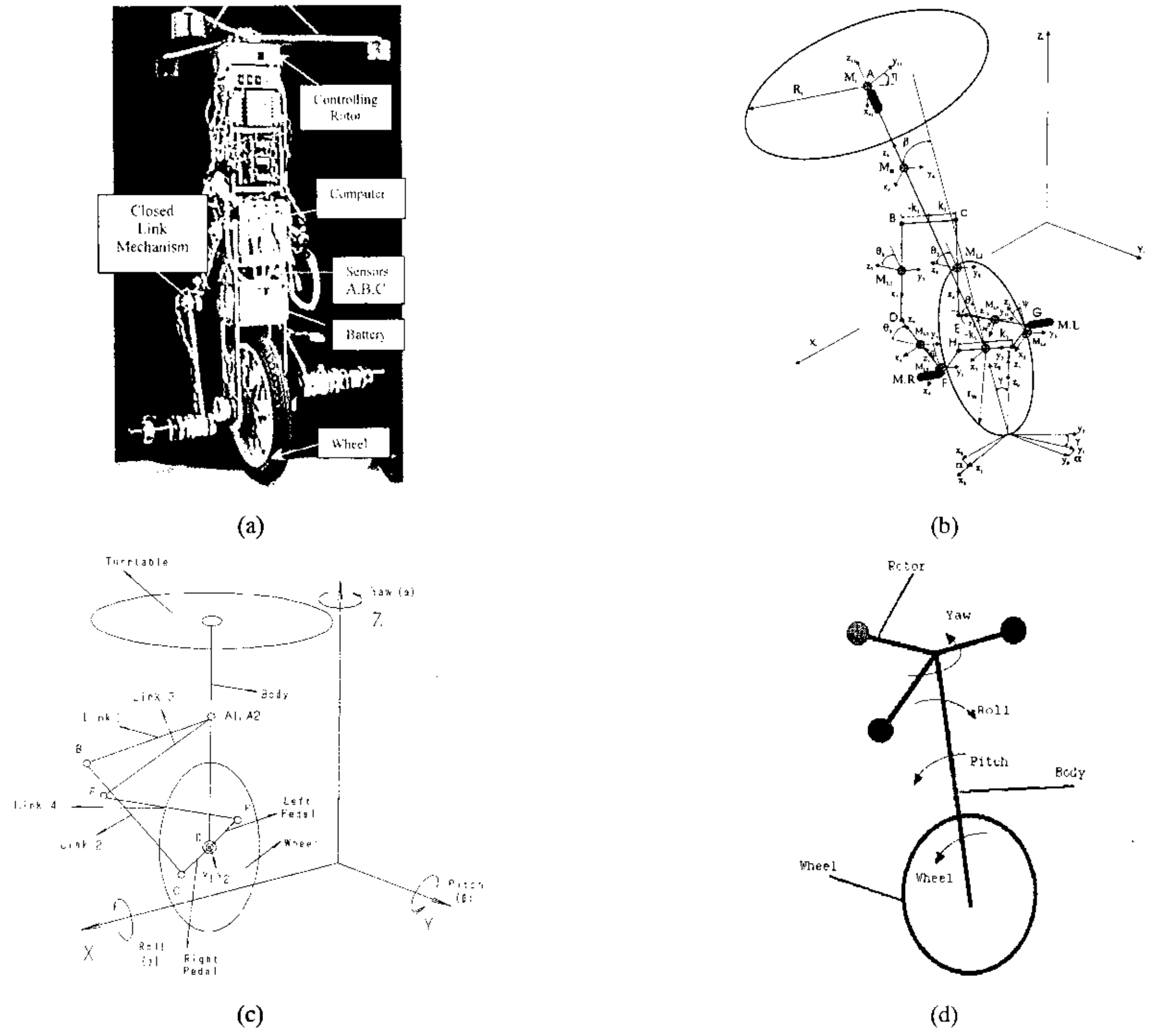


Fig. 6. a) Photo of Extension-Cableless Robotic Unicycle; b) Coordinate Describing the Unicycle Model; c) Complicated Model for Emulating Human Riding of a Unicycle Model. d) Simple Model for Emulating Human Riding of a Unicycle Model.

the periphery sensors. Second, the controlled object in posture control and locomotion is physically unstable, similar to an inverted pendulum, and feedback control is intelligent computation essential for the cerebellum for adaptive posture control. The vermis receives information about position, velocity, and acceleration of the head and torso from proprioceptors, visual sensors, and the vestibular organ. Its output is directed mainly to the medial brainstem and axial regions of the motor cortex. Based on this physiological and anatomical interpretation, we developed a block diagram (Fig.2).

2.2. Vestibular System as Control of Extension-Cableless Robotic Unicycle

In the design of a robot model (**Fig.6**a) at the executive biomechanical level (Fig.2), the rotor consists of 3 bars each 285mm long allocated radially from the rotor center. On the tip of each bar is a weight ($0.9kg$) fixed symmetrically as a symmetric rotor. Using the 4-bar closed links (Fig.6b,c) enables robot posture stability in pitch because acceleration compensation in this direction is attained by the cooperative action of the link mechanisms and rotor. Pitch stability is maintained despite changes in rotor and wheel velocity or acceleration (Fig.6b-d). Fig.6d shows the simple unicycle model.

Remark 3. Our study of rider stability control on a unicycle began by observing and analyzing logical behavior of a human riding unicycle based on a vestibular biomechanical model (Fig.2) and an intelligent thermodynamic model (qualitative physical representation) including instinct and intuition as logical decision making. We found that the rider's thighs and shanks for a 2 closed link loop that plays an important role in the rider's postural stability control on a unicycle (Fig.6a-c). Using this, we developed a logic biomechanical model with 2 closed links and 1 turntable (rotor) to emulate a human riding unicycle by a robot including intuition and instinct control of body behavior based on soft computing. Intuition and instinct are considered as global and local search mechanisms for optimum solution of intelligent behavior and realized based on GA and FNN. For the GA fitness function, a new physical measure is minimum entropy production for describing intelligent thermodynamic behavior in a biomechanical model. We provide a general measure to estimate mechanical controllability qualitatively and quantitatively, whatever the control scheme. The measure is computed using a Lyapunov function coupled with the changed entropy rate, interrelating between the skill of the human operator driving the unicycle (minimum physical expense) and quality of robotic unicycle control (**Fig.7**).

The interrelation between the Lyapunov function (stabil-

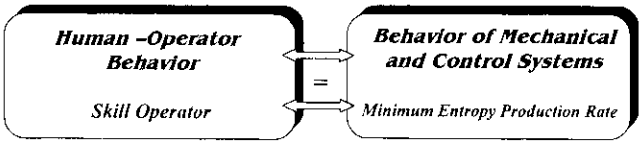


Fig. 7. Conceptual Interrelation

ity) and the entropy production rate of motion (controllability) in the internal biomechanical model is the mathematical background for designing soft computing algorithms for intelligent control of a robotic unicycle. Our work deals with improving fuzzy simulation of robust intelligent control with a minimum entropy production rate based on soft computing including GA and FNN.

3. Qualitative Physics and Thermodynamic Equations of Motion for the Extension-Cableless Robotic Unicycle Model

First, for internal world representation of an artificial robotic unicycle life, we develop thermodynamic equations of motion. The robot's postural stability control is analyzed and results compared to computer simulation.

Thermodynamic equations of motion for the robotic unicycle with a symmetric rotor are given[8] as follows,

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

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

The parameters of Eqs.(1) and (2) are described in Ref.8) in detail. In Eq.(2) S_u is the entropy of the robot unicycle's motion and S_c is the entropy of both controllers, τ_d are dissipate parts of the control torque (for the PD-controller the dissipate part is described by $k_i(\dot{\gamma}, \dot{\beta})$). The algorithm for entropy production calculation in the dynamic dissipate systems is described.[11,12] For stability analysis and computer simulation of the robotic unicycle's dynamic behavior, Eq.(1) are rewritten in the conventional form of ordinary differential equations as $\dot{q}_i = \varphi_i(q_i, \tau, t)$.

Analysis indicates that the longitudinal and lateral stability domain is a strange attractor.[6] Both are mutually influenced, so the unicycle is essential nonlinear with its nonlinear cross braces. This aids in understanding experimental results with the galvanic vestibular stimulus for analyzing postural adaptation and stability for the unicycle.[10] It also shows that the improved model is closer to a human riding unicycle as an intelligent robotic system.

Lyapunov Function and Thermodynamic Conditions for Stability of the Robotic Unicycle. To analyze robot model stability as essentially nonlinear, we use the asymptotic method of a Lyapunov function and qualitative physics taking advantage of the interrelation between Lyapunov and entropy production rate functions.[11] The approach to defining the Lyapunov function is also used. The Lyapunov function for the system (1) defined as $V = \frac{1}{2}(\sum_{i=1}^{6} (q_i^2 + S^2))$, where $S = S_u - S_c$ and $q_i = (\alpha, \gamma, \beta, \dot{\alpha}, \dot{\gamma}, \dot{\beta})$. Here we use[10] the following interrelation between the Lyapunov function and entropy production for an open system such as a unicycle

$$\frac{dV}{dt} = \sum_{i=1}^{6} q_i \varphi_i(q_i, \tau, t) + (S_u - S_c)\left(\frac{dS_u}{dt} - \frac{dS_c}{dt}\right) < 0. \quad (3)$$

From Eq.(3), necessary and sufficient conditions for Lyapunov stability of a robotic unicycle are expressed as

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

i.e., stable motion of a unicycle is achieved with "negentropy" $-S_c$ (in *Brillouin's* terminology[2]) and the change of negentropy rate $\frac{dS_c}{dt}$ in the control system must be subtracted from the change in entropy production rate $\frac{dS_u}{dt}$ in the motion of the robotic unicycle with the second condition in Eq.(4). From Eq.(4), the stability measure for the robotic unicycle is obtained by computing the minimum entropy production rate of the system and controllers.

Remark 4. From qualitative physics, internal world representation of the robotic unicycle has 2 unstable states – 1) local unstable kinematic equilibrium in the lateral plane (angle of rolling γ) and 2) a global unstable dynamic state in the longitudinal plane (angle of pitch β). The 2 correlation states must be controlled with 2 fuzzy controllers[4] – necessary and sufficient conditions for improving control stability of our robotic unicycle. Approximate reasoning such as fuzzy implication A → B realized on FNN plays the role of a local coordinator between lookup tables of 2 controllers with parallel-sequential data processing. Coordinated action between lookup tables of these 2 fuzzy controllers is made with GA and FNN. Two fuzzy controllers control transfer energy with minimum entropy from lateral to longitudinal planes using dynamic nonlinear cross braces in the robotic unicycle model (compensation of transfer energy from unstable dynamic motion "in large" (Fig.2) to longitudinal plane based on Eq.(3)). The fuzzy controller in the lateral plane acts as if ridden by a human operator by organizing special *parametric* excitation in nonlinear cross braces.[9] These parametric excitations generate energy compensating for transfer energy from the longitudinal plane in an unstable state. The unstable state "in small" compensates for the unstable state "in large" (Fig.2). Stable motion of the robotic unicycle model results from nonlinear control on an intelligent level of correlated energy transfer between 2 unstable virtual states. The 2 adaptive fuzzy controllers self-organize control stability on a robotic unicycle using intuition and instinct. We obtain the physical model describing quantum fuzzy logic controllers in the general form of quantum fuzzy logic controllers for biomechanical systems.[13] Feedback gains for fuzzy PD controllers were adapted.[3,4,6]

4. Fuzzy Intelligent Control of the Extension-Cableless Robotic Unicycle with Soft Computing Based on GA and FNN

In our AI control system,[8] 2 gain schedule PD-controllers are used – one for the symmetric rotor and one for closed link mechanisms. Control torque to the symmetric rotor is given as

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

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. Control torque applied to links 2 and 4 are given as

$$\tau_{\theta 3} = -\tau_{\theta 4} = -kp_1 \times k_1 \times \beta - kd_1 \times k_2 \times \dot{\beta}, \quad \ldots \ldots (6)$$

where $\tau_{\theta 2}$ and $\tau_{\theta 4}$ are the torques to links 2 and 4; kp_1 and kd_1 are constant feedback gains; and k_1 and k_2 are fuzzy values changed in [0,1] with FNN.

Remark 5. Biomechanical analysis of posture stability shows[10] that PD control represents the minimum complexity required for stable posture control. Component P (proportional) contains antigravitational forces and compensates for position errors. Component D (derivative) is anti-Coriolis compensation and provides damping action. Parameters (kp_1, kp_2) are interpreted as a stiffness (spring constant) arising from passive and active muscular forces, whereas (kd_1, kd_2) is compared to viscous damping as obtained with a wheel dashpot. Suffice it to say that this is the minimum complexity anticipated for a stabilized robotic unicycle model.

Fuzzy tuning rules for k_1, k_2, k_3 and k_4 are formed by the learning system of a FNN.[8] Fuzzy controllers are hierarchical, 2-level control systems intelligent "in small" (Fig. 2).[14] The lower (execution) level is the same as a conventional PD controller and the upper (coordination) level consists of a KB with a fuzzy inference module as production rules with fuzzy implication, fuzzification, and defuzzification components.

5. Simulation Results Due to the New Physical Measure for Mechanical Controllability

Using the proposed control, we conducted computer simulation. In the first case, GA simulates an intuition mechanism choosing the optimum structure of the PD controller, using the capacity of the fitness function, which is the measure of the entropy production rate and the evolution function, which is entropy.[8]

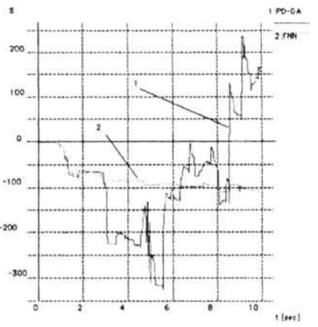
5.1. Simulation Results

Figure 8 shows simulation results of the temporal thermodynamic behavior of the robotic unicycle with PD-GA-controllers and a FNN-controller for the complicated robotic unicycle model. To calculate entropy production rate $\frac{dS_\alpha}{dt}$ (yawing angle), $\frac{dS_\beta}{dt}$ (pitching angle), $\frac{dS_\gamma}{dt}$ (rolling angle), we used 452, 201, and 409 dissipative terms. From simulation results, we found that relation $\frac{dS_c}{dt} > \frac{dS_u}{dt}$ from Eq.(4) is true and the GA finds optimum parameters for PD controllers with a simple structure using the minimum entropy production rate. The FNN controller offers a more flexible controller structure with smaller torques, and learning produces less entropy (Fig.8) than GA: *An instinct mechanism produce less entropy than an intuition mechanism.* Time required to get optimum control with learning on a FNN (instinct) is longer than with a global search on GA (intuition).

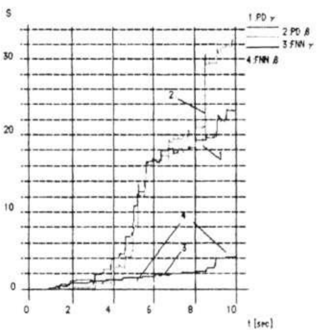
Figure 9 show simulation results for mechanical (phase portraits) and thermodynamic behavior of the robotic unicycle with FNN-PD controllers for the complicated unicycle model with new model parameters.

Figure 10 shows 3D simulation results of mechanical and thermodynamic behavior of the robotic unicycle with PD-GA-controllers for the simple unicycle model.

These results confirmed finding the optimum decision in an application hybrid FPD for changing parameters of feedback based on approximate reasoning, based in turn on the minimum entropy production rate as a physical measure of control quality. As results show, the entropy production rate in rotor control is greater than in link control, as is proved by experiments below.

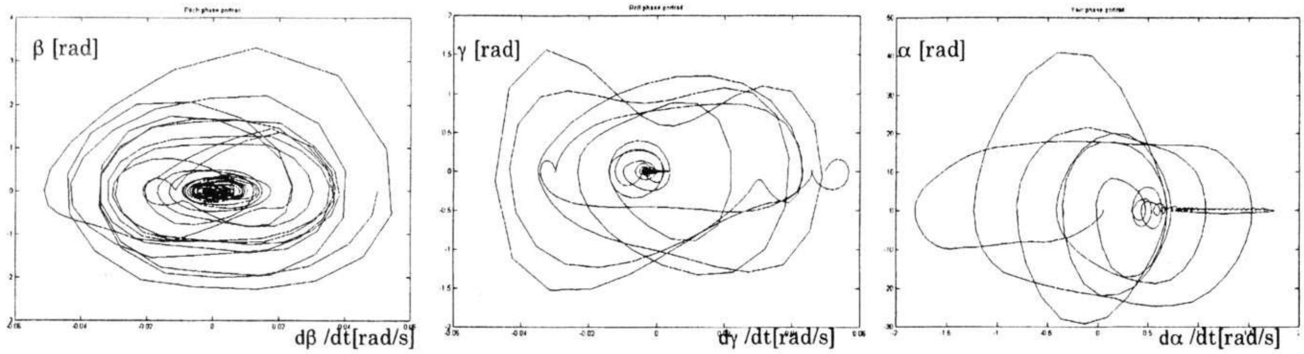


Temporal thermodynamic behavior of the Yaw.

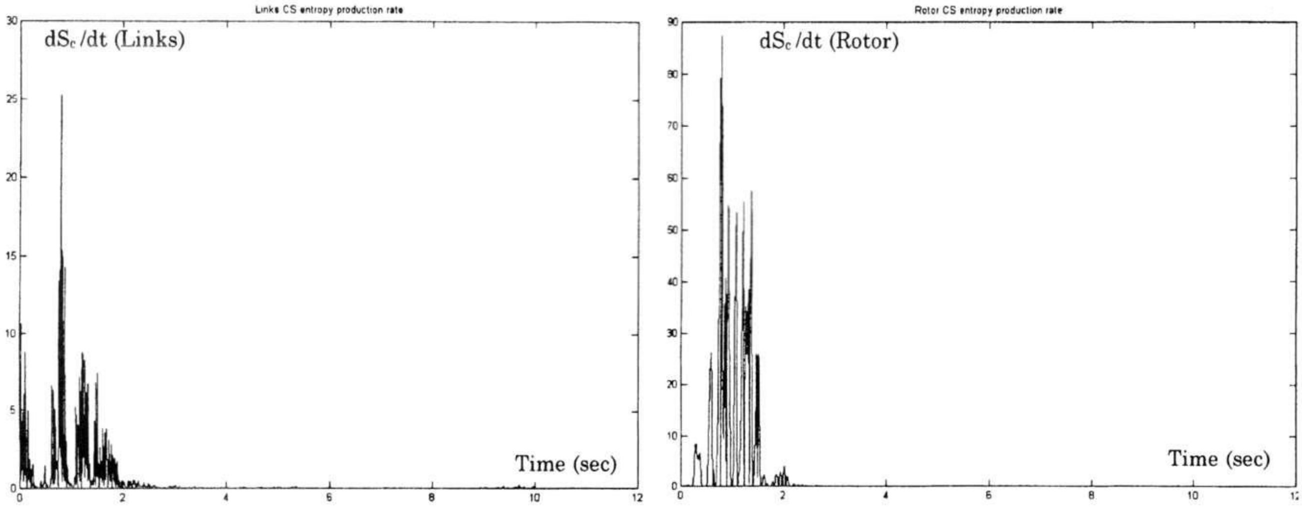


Temporal thermodynamic behavior of the Pitch & Roll.

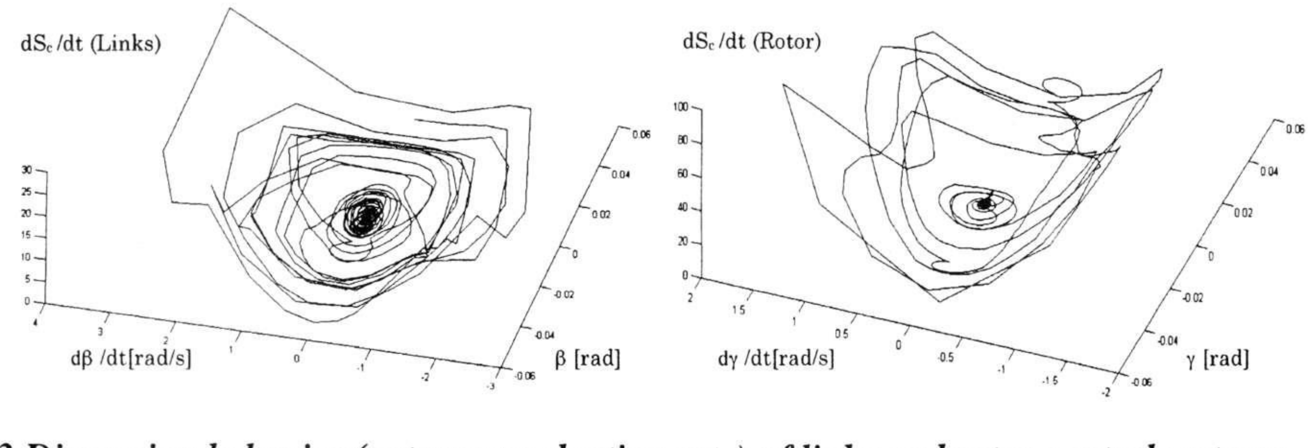
Fig. 8. Simulation of Thermodynamic Behavior of Control in Yaw, Pitch, and Roll



Phase portraits of Pitch, Roll & Yaw Dynamic



Temporal thermodynamic behavior (entropy production rate) of links and rotor control systems.



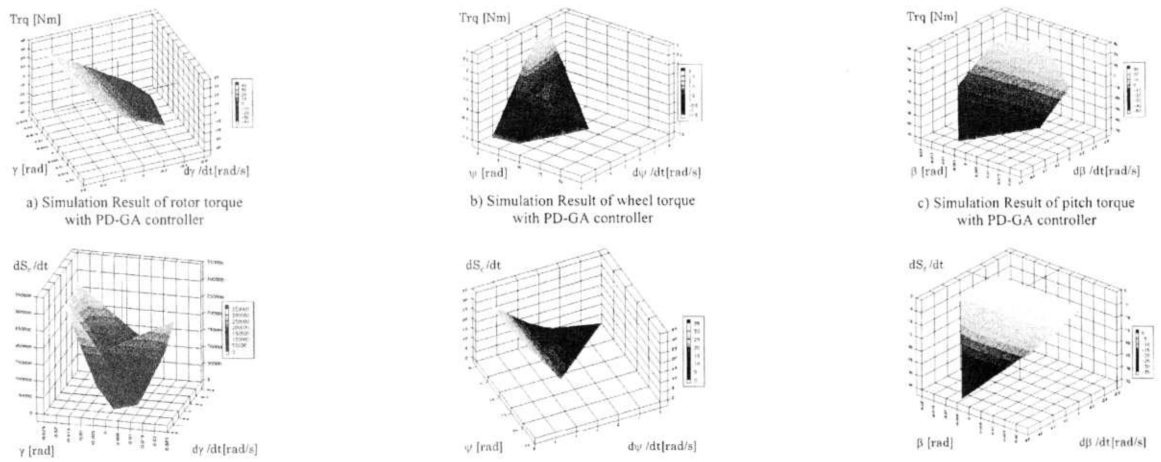
3 Dimension behavior (entropy production rate) of links and rotor control systems

Fig. 9. Simulation of Robotic Unicycle Control and Entropy Production Rate with FNN-PD Controller for Complicated Mathematical Model with New Model Parameters

For the fuzzy gain schedule, hybrid PD controllers are proposed in Ref.5) for the robot's postural stability control. Simulation based on the FNN with the minimum entropy production rate are used to obtain lookup tables for feedback gains that change fuzzy rules of approximate reasoning. This enables us to use instinct and emotion during the experiment without calculating them in real time. For the robotic unicycle, we use this for a fuzzy gain schedule PD-controller.

5.2. Simulation Results for Fuzzy Gain PD-Controllers

In deriving dynamic equations of motion for the robot, coordinates of the new robot configuration are shown in



a) Simulation Result of rotor torque with PD-GA controller

b) Simulation Result of wheel torque with PD-GA controller

c) Simulation Result of pitch torque with PD-GA controller

d) Simulation Result of entropy production rate of rotor PD-GA controller

e) Simulation Result of entropy production rate of wheel PD-GA controller

c) Simulation Result of entropy production rate of pitch PD-GA controller

Fig. 10. Simulation of Unicycle Control and Entropy Production Rate in PD-GA Controller for Simple Mathematical Model

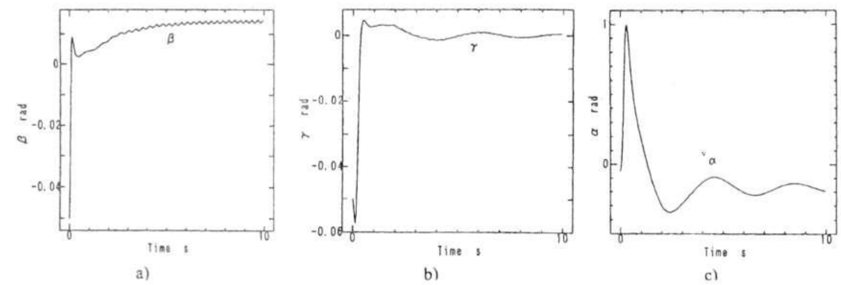


Fig. 11. Simulation for 2 Fuzzy Gain Schedules PD Controllers for Complicated Model: a) Pitch Angle; b) Roll Angle; c) Yaw Angle

Fig.6b.

Results obtained with 2 fuzzy gain schedule PD controllers. We consider 2 fuzzy gain schedule PD controllers – one is for the rotor and one for closed-link mechanisms. The torque to the rotor is the same as that in Eq.(5) and the torque to links 2 and 4 is given in Eq.(6).

Simulation (Fig.11) showed that the proposed control is effective in achieving postural stability maintained over a fairly long time. Simulation results show that the roll angle is efficiently stabilized around zero and the pitch angle stabilized around a small positive value, indicating a need to stabilize pitch angle at a small positive value, not zero, to maintain postural stability.

Comparison with results above indicates postural stability is not influenced much by the robot's initial posture. Simulation results show postural stability is achieved if both initial pitch angle $|\beta|$ and initial roll angle $|\gamma|$ are less than 0.1 rad.

6. Experimental Results

The new extension-cableless robotic unicycle (Fig.6a) consists of a wheel with 2 cranks, a main body, an overhead rotor, and 2 closed links on both sides of the wheel. The closed link mechanism is used for a longitudinal stability and the symmetric rotor for lateral stability. Four motors were used for the complicated model, and only 3 motors for the new extension-cableless unicycle model. For the old complicated[4,5] model, the wheel was driven through a ball reduction gear, a couple of spiral bevel gears, and a timing belt by a DC servomotor (60W) inside the robot. Now the wheel is driven through close link motors. The rotor is driven by a harmonic drive motor (old: 34W, new: 60W) installed on the body (Fig.6b). Left and right closed links are driven directly by harmonic drive motors (old: 20.3W, new: 60W) on links 2 and 4 (Fig.6a,b). Links motors are the same for the symmetric geometrical structure and balance of the robot.

A 32-bit personal computer is the system controller. The wheel, symmetric rotor, and closed link mechanisms are driven by torque-controlled motors with software servocontrol. Control programs are written in C.

Three rate gyrosensors (A, B and C) (Fig.6a) on the 3 principal axes of the robot measure angular velocities of inclination in pitch, roll, and yaw directions. The resolution of the angular velocity of the sensors is 0,1deg/s. An optical rotary encoder (500 pulses/revolution) on each servomotor detects the angle caused by rotation of servomotors. The coordinates defined in Fig.6b enable us to calculate the robot's posture or Euler's angle (α, β, γ) to global reference coordinates measured from angular velocity ω_x, ω_y, and ω_z by 3 rate gyrosensors as in Eqs.(7)-(9),

$$\alpha = \int((\omega_x \cos\beta - \omega_x \sin\beta)\cos^{-1}\gamma)dt, \quad \ldots\ldots\ (7)$$

$$\beta = \int(\omega_y - (\omega_z \cos\beta - \omega_x \sin\beta)\tan\gamma)dt \quad \ldots\ldots\ (8)$$

$$\gamma = \int(\omega_x \cos^{-1}\beta + (\omega_z \cos\beta - \omega_x \sin\beta)\tan\beta)dt, \quad \ldots\ (9)$$

where ω_x is the angular velocity related to Px_6, ω_y is the angular velocity related to Py_6, and ω_z is the angular velocity

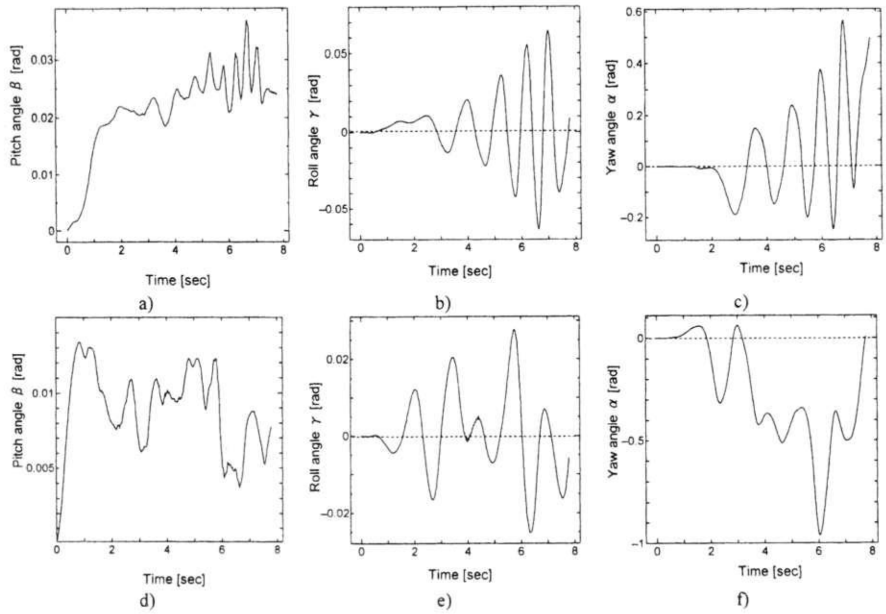


Fig. 12. Experimental Results of Temporal Behavior of a, d) Pitch Angle; b, e) Roll Angle, and c, f) Yaw Angle for Different Tests

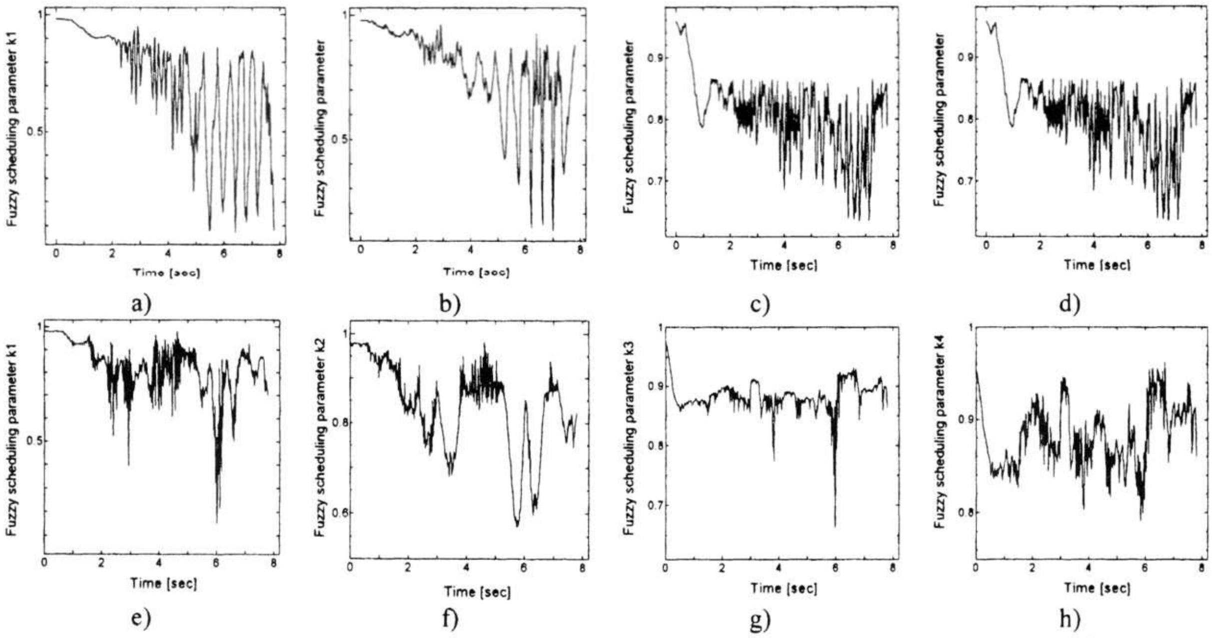


Fig. 13. Experimental Results of Temporal Behavior of Fuzzy Gains a, e) k_1; b, f) k_2; c, g) k_3; d, h) k_4, for Different Tests

related to Pz_6 (Fig.6b).

Using small rate gyrosensors adds drift on output due to time and change of temperature. Drift may adversely affect calculation of postural angles in the experiment, so we selected sensors with the smallest drift. Experiments were conducted in 8 seconds because drift in sensor output is not so high.

Remark 6. Because the old robot model wheel was aluminum, we had to deal with friction between the wheel and ground. To keep the unicycle wheel from slipping, we use a 3.0m × 9.0m synthetic rubber carpet. The unicycle's initial posture is set by the operator and ground unevenness is random, so we could not repeat exactly the same results in experiments even with the same control and feedback gains.

Figures.12-14 show experimental results for the new cableless unicycle model in beginning of experiments (up line) and now presented (down line), achieving lateral stability (stability in the roll direction). Figure 12c,f shows that the robot posture in the yaw direction changes quickly in the experiment because yaw control ensures lateral stability, the change in ground unevenness changes the robot's lateral posture and this change in the roll direction requires a change in robot posture in the yaw direction. Figure 14 shows temporal and 3D thermodynamic behavior (entropy production rate) for 2 experiments (Figs.12 and 13). From Fig.14a,c,e,g, we concluded that entropy production rates in link mechanisms are less than in the rotor (the body produces more entropy than the feet). Experimental results also indicated that temporal behavior in experiments (Fig.14c,g) obtained using the minimum entropy production rate in control is more intelligent than in Fig.14a,e using only FPD.

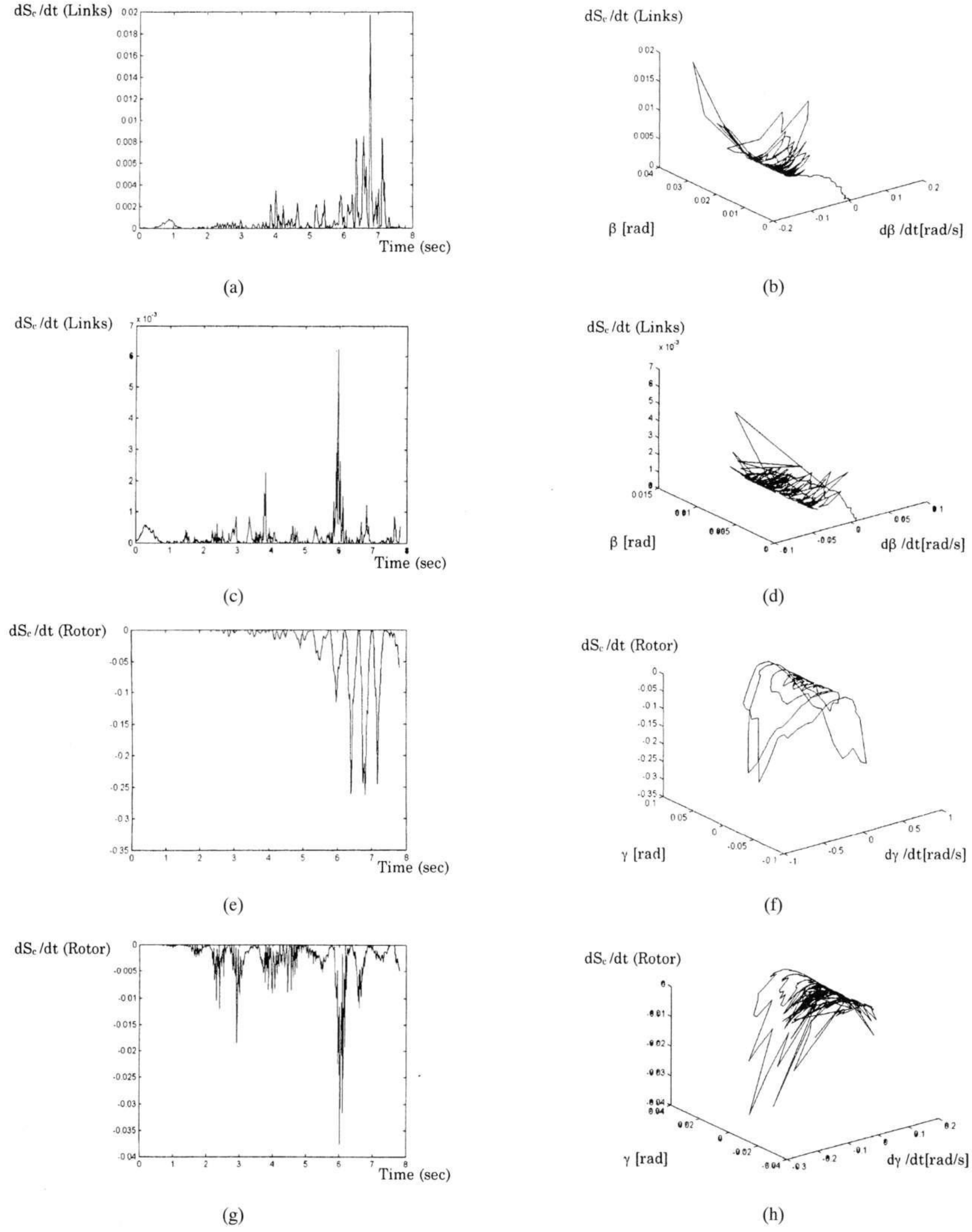


Fig. 14. Temporal and 3D Thermodynamic Behavior (Entropy Production Rate): a, b, c, d) Links and e, f, g, h) Rotor Control for 2 Different Tests

The wheel's average speed is about 1.2m/s, similar to that of a human rider on a unicycle.

Figure 6a shows the robot's posture during an experiment. The initial posture is set by the operator, who removes a hand immediately after the wheel starts to go forward. Comparing results in Ref.4) and here, we find it much easier to achieve the robot's posture stability with fuzzy gain schedule PD-controllers. If the initial posture of the robotic unicycle is near the ideal stable posture (β = 0.0 rad and γ = 0.0 rad), postural stability is obtained in almost all trials. Postural stability with 2 fuzzy gain schedule PD controllers is achieved even if posture is randomly disturbed to some extent by the ground conditions because 2 fuzzy gain schedule PD controllers recover from roll angles as big as in Fig.10b,e while PD control of the unicycle cannot. Such recovery shows the excellence of 2 fuzzy gain schedule

PD-controllers. Proposed control efficiently improves postural stability and controllability. Figure 13 shows temporal behavior of fuzzy gains k_1, k_2, k_3, and k_4. Figure 14 shows increasing unicycle skill operation. The physical measure of skill operation decreases the entropy production rate of the control system.

7. Conclusions

We presented robust robotic unicycle intelligent control with a background of qualitative physical analysis of the unicycle's dynamic motion and the introduction of an intelligent level at the control system by realizing instinct and intuition based on FNN and GA. The main components of AI control are based on soft computing and fuzzy robust control. We adapted 2 FPD controller parameters to achieve stable motion of the unicycle over a long (finite) time without changing the structure of the executive level of control using soft computing. We introduced 2 new mechanisms to intelligent control based on a minimum entropy production rate in the robotic unicycle's motion and the control system itself. Simulation of thermodynamic equations of motion and intelligent control confirmed the effectiveness in handling the system's nonlinearity of the robot's postural stability control. The robotic unicycle model is a *new benchmark* for intelligent fuzzy controlled motion of a nonlinear dynamic system with 2 (local and global) unstable states. The use of a fuzzy gain schedule PD controller with lookup tables calculated by FNN offers the use of instinct and intuition in real time to achieve successful experimental results.

References:

1) H. Gomi and M. Kawato, "Adaptive feedback control models of the vestibulocerebellum and spinocerebellum," Biological Cybernetics, **65**, 105-114, (1992).
2) B.N. Petrov, G.M. Ulanov, S.V. Ulyanov and E.M. Khazen, "Informational and Semantic Problems in Control Processes and Organization" (In Russian), Nauka Publ., Moscow, (1977); and B.N. Petrov, I.I. Goldenblat and S.V. Ulyanov, "Model Theory in Control: Thermodynamic and Information Approach," (In Russian), Nauka Publ., Moscow, (1978).
3) M. Lauk, C.C. Chow, A.E. Pavlik and J.J. Colloins, "Human balance out of equilibrium: Non-equilibrium statistical mechanics of posture control," Physical Review Letters, **80**-2, 413-416, (1998).
4) Z.Q. Sheng, K. Yamafuji and S.V. Ulyanov, "Study on the stability and motion control of a unicycle. Pts 3,4,5," JSME International Journal, **39**-3, 560-568; 569-576, (1996); and Journal of Robotics & Mechatronics, **8**-6, 571-579, (1996).
5) S.V. Ulyanov, Z.Q. Sheng and K. Yamafuji, "Fuzzy Intelligent control of robotic unicycle: A New benchmark in nonlinear mechanics," Intern. Conf. on Recent Advanced Mechatronics, Istanbul, Turkey, **2**, 704-709, (1995).
6) S.V. Ulyanov, Z.Q. Sheng, K. Yamafuji, S. Watanabe and T. Ohkura, "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, (1995).
7) S.V. Ulyanov and K. Yamafuji, "Fuzzy Intelligent emotion and instinct control of a robotic unicycle," 4th Intern. Workshop on Advanced Motion Control, Mie, Japan, **1**, 127- 132, (1996).
8) S.V. Ulyanov, S. Watanabe, K. Yamafuji and T. Ohkura, "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 on Fuzzy Systems and Soft Computing (ICAF'96), Siegen, Germany, pp.49-58, (1996).
9) S.V. Ulyanov, Q. Feng, K. Yamafuji and V.S. Ulyanov, "Stochastic analysis time-variant nonlinear dynamic systems, Pts 1,2," Probabilistic Engineering Mechanics, **13**-3, 183-204; 205-226, (1998).
10) S.V. Ulyanov, S. Watanabe, V.S. Ulyanov, K. Yamafuji, L.V. Litvintseva, and G.G. Rizzotto, "Soft computing for the intelligent control of a robot unicycle based on a new physical measure for mechanical controllability," Soft Computing, **2**-2, 73-88, (1998).
11) S.V. Ulyanov, K. Yamafuji, V.S. Ulyanov, T. Fukuda and I. Kurawaki, "Interrelation between entropy production and Lyapunov stability of relaxation processes in nonlinear closed dissipative dynamic system," Physics Letters A (accepted), (1998).
12) S.V. Ulyanov, K. Yamafuji, V.S. Ulyanov, T. Hagiwara and I. Kurawaki, "Computational intelligence for robust control algorithms of complex dynamic systems with minimum entropy production. Part I: Simulation of entropy-like dynamic behavior," this issue, (1999).
13) I.P. Ionov, O.I. Vasileva and S.V. Ulyanov, "Dual control of artificial ventilation of lungs (AVL) process using a fuzzy quantum controller in the feedback circuit," Biomedical Engineering, **23**-1, 7-17, (1990); and P.S. Kantor, S.V. Ulyanov, A. Pagni and G.G. Rizzotto, "Fuzzy quantum controller on WARP for artificial ventilation of lungs," Proc. of ICAFS'94 (Inter. Conf. on Application of Fuzzy Systems), Tabriz, Iran, 233-235, (1994).
14) V.N. Zhakharov and S.V. Ulyanov, "Fuzzy models of intelligent industrial controllers and control systems. Pts 2,3," Journal of Computer and Systems Sciences International, **33**-2, 94-108; 117-136, (1995).

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