Computer Science Journal of Moldova, vol.**21**, no.2(62), 2013

Intelligent Self-Organized Robust Control Design based on Quantum/Soft Computing Technologies and Kansei Engineering

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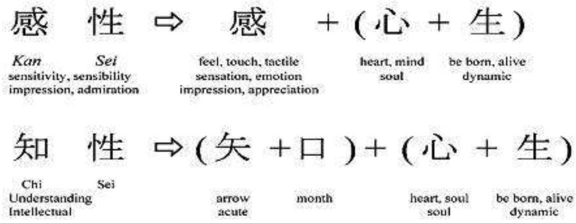
Abstract

System of systems engineering technology describes the possibility of ill-defined (autonomous or hierarchically connected) dynamic control system design that includes human decision making in unpredicted (unforeseen) control situations. Kansei/Affective Engineering technology and its toolkit include qualitative description of human being emotion, instinct and intuition that are used effectively in design processes of smart/wise robotics and intelligent mechatronics. In presented report the way how these technologies can be married using new types of unconventional computational intelligence is described. System analysis of interrelations between these two important technologies is discussed. The solution of an important problem as robust intelligent control system design based on quantum knowledge base self-organization in unpredicted control situations and information risk is proposed. The background of applied unconventional computational intelligence is soft and quantum computing technologies. Applications of the developed approach in robust integrated fuzzy intelligent control systems are considered using concrete Benchmarks.

Keywords: Kansei/Affective engineering, system of systems engineering, smart robot, emotion, instinct, intuition, soft computing, quantum computing, quantum fuzzy inference.

1 Introduction

Lee showed the etymology of the term *Kansei* and compared it to another word: *Chisei* (Lee 2002) as following



It "shows the etymology of *Kansei* and *Chisei* interpreted from the Chinese characters, both of which are processed in human minds when they receive the information from the external world. Chisei works to increase the knowledge or understanding which is matured by verbal description of logical facts. And *Kansei* works to increase the creativity through images with feelings or emotions" (Lee 2002) [1].

Harada (1998) proposed five major dimensions of Kansei:

- *Kansei* is a subjective and unexplainable function.
- *Kansei*, besides its innate nature, consists of the cognitive expression of acquired knowledge and experience.
- *Kansei* is the interaction of intuition and intelligent activity.
- *Kansei* is the ability of reacting and evaluating external features intuitively.
- *Kansei* is a mental function creating images.

The previously analyzed definitions indicate that [1]:

- *Kansei* process gathers the functions related to emotions, sensitivity, feelings, experience, intuition (i.e. sensory qualities related functions (Clark 1996)), including interactions between them.
- *Kansei* means are all the senses (sight, hearing, taste, smell, touch, balance, recognition...) and – probably – other internal factors (such as personality, mood, experience, and so on).

- *Kansei* result is the fruit of *Kansei* process (i.e. of these function processes and of their interactions). It appears to be a unified perception providing a qualitative meaning and value of one's direct environment. In other words, *Kansei* result is how one perceives qualitatively one's environment. Therefore, *Kansei* result is a synthesis of sensory qualities.

Figure 1 intends to describe the *Kansei* process [1].

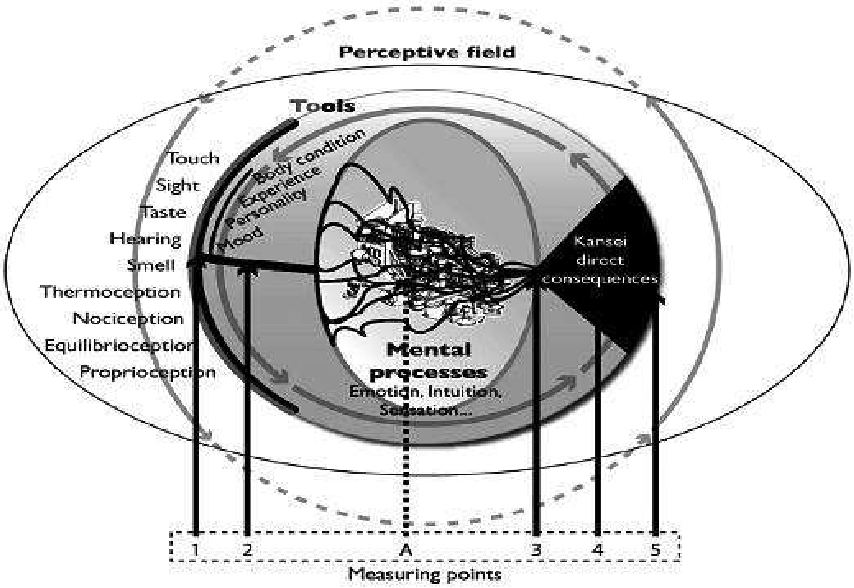


Figure 1. Comprehensive view on Kansei

We considered the humanized technology of intelligent robotic systems design based on Kansei /Affective Engineering and System of Systems Engineering using Quantum/Soft Computing as unconventional computational intelligence toolkit. As well known the subject of humanized technology or human-related systems has been actively researched.

With the increasing concern regarding human factors in system development Kansei Engineering and Soft Computing are the most representative research fields on this subject [2 – 5]. Soft computing toolkit is developed for emotion, instinct, and intuition recognition and expression generation [3, 6].

In particular, with genetic algorithm – GA – (as effective random search of solution) an intuition process (optimization) is modeled.

Fuzzy neural network (FNN) is used for description of instinct process (adaptation and learning) that modeled approximation of optimal solution in unpredicted control situation.

Fuzzy logic control is used for design of an emotion according to corresponding designed look-up table.

Quantum control algorithm of self-organization is the background of wise robotic control system design. Quantum computing toolkit is used for increasing of robustness in intelligent control systems (especially for unpredicted control situations).

Figure 2 demonstrates the main idea of this approach and the creation of quantum intelligent design IT.

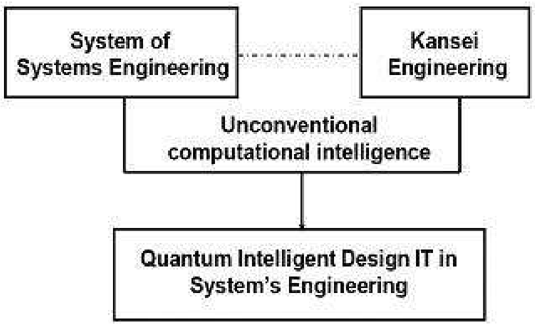


Figure 2. Structure background of quantum intelligent design IT

In recent years, the concept of self-organization has been used to understand collective behavior of human being society, animals, ants, birds, bacterial colonies, quantum dots etc. The central tenet of self-organization is that simple repeated interactions between individuals can produce complex adaptive patterns at the level of the group. Inspiration comes from patterns seen in physical systems, such as chemical waves, which arise without complexity at the level of the individual units of which the system is composed.

A general characteristic of self-organizing systems is as following: they are *robust* or *resilient*.

This means that they are relatively insensitive to perturbations or errors, and have a strong capacity to restore themselves, unlike most human designed systems.

One reason for this fault-tolerance is the *redundant*, *distributed* organization: the non-damaged regions can usually make up for the damaged ones.

Another reason for this intrinsic robustness is that self-organization thrives on *randomness*, fluctuations or "noise". A certain amount of random perturbations will facilitate rather than hinder self-organization.

A third reason for resilience is the stabilizing effect of *feedback* loops.

The present report reviews and analyses its most important engineering concepts and principles of self-organization that can be used in design of robust intelligent control systems.

Analysis of self-organization models gives us the following results.

Models of self-organization include natural *quantum* effects and based on the following *information-thermodynamic* concepts: (i) macro- and micro-level interactions with information exchange (in ABM micro-level is the communication space where the inter-agent messages are exchanged and explained by increased entropy on a micro-level); (ii) communication and information transport on micro-level ("quantum mirage" in quantum corrals); (iii) different types of quantum spin correlation that design different structure in self-organization (quantum dot); (iv) coordination control (swam-bot and snake-bot).

Natural evolution processes are based on the following steps:

(i) templating; (iii) self-assembling; and (iii) self-organization.

According to quantum computing theory in general form every quantum algorithm (QA) includes the following unitary quantum operators: (i) superposition; (ii) entanglement (quantum oracle); (iii) interference. Measurement is the fourth classical operator. [It is irreversible operator and is used for measurement of computation results].

Quantum control algorithm of self-organization that is described below is based on quantum fuzzy inference (QFI) model [7]. QFI includes these concepts of self-organization and is realized by corresponding quantum operators.

Structure of QFI that realize the self-organization process is developed. QFI is one of possible realization of quantum control algorithm of self-organization that includes all of these features: (i) superposition; (ii) selection of quantum correlation types; (iii) information transport and quantum oracle; and (iv) interference.

With *superposition* a *templating* operation is realized based on macro- and micro-level interactions with information exchange of active agents. *Selection* of quantum correlation type organises *self-assembling* using power source of communication and information transport on micro-level. In this case the type of correlation defines the level of *robustness* in designed KB of FC. *Quantum oracle* calculates intelligent quantum state that includes the most important (value) information transport for *coordination* control. *Interference* is used for extraction the results of coordination control and design in on-line robust knowledge base (KB). The developed QA of self-organization is applied to design of robust KB of fuzzy controller (FC) in unpredicted control situations. Main operations of developed QA and concrete examples of QFI applications are described.

We considered more concrete integrated fuzzy intelligent control systems (IFICS) for smart / wise robotic system design using quantum control algorithm of KB self-organization. Principles of minimum entropy production in robotic system behavior and minimum of information entropy relative to quantum knowledge are used. New effect of artificial intelligence as the design in on-line of a robust FC from the responses of two unstable FCs in unpredicted control situations is demonstrated.

In particular, the application of QFI to design of robust KB in fuzzy PID-controller is showed on example of robust behavior design in global unstable non-linear control objects as "cart - pole" system. For locally unstable control object (with weak and rough defined structure) the robustness of sub-optimal solutions of control laws are demonstrated. Quantum FC based on QFI in both cases showed the increasing robustness in complex unpredicted control situations. Surprisingly that *robust* quantum FC is designed in this case (in on-line) from *finite number* of FCs (designed in off-line) that everyone are *non-robust* in considered unpredicted control situation. For locally and globally unstable control objects, two and three KBs designed with soft computing optimizer correspondingly, are used. It is a new quantum effect – the reduction of redundant classical information in control laws of coefficient gain schedule in PID-controller – by using a value information extracted on-line with new types of quantum correlations from responses of fuzzy PID-controllers (with fixed knowledge bases) on unpredicted control situation.

In general, these are also new design effects in advanced control technology and in design technology of intelligent control system based on self-organization realization with QFI.

2 Background

Ideas from biology and self-organization can strongly benefit the design of smart autonomous robots. Autonomous robots, perceived as congeners and acting as interactive decoys, are interesting research tools. By their ability to respond and adapt to animal behavior, they open possibilities to study individual and social animal behaviors. Robots, or any artificial agents, could then be used to implement new feedback loops, leading to new collective patterns in these mixed natural artificial systems [8 – 10].

Biological organisms have evolved to perform and survive in a world characterized by rapid changes, high uncertainty, indefinite richness, and limited availability of information.

Industrial robots, in contrast, operate in highly controlled environments with no or very little uncertainty. Although many challenges remain, concepts from biologically inspired (bio-inspired) robotics will eventually enable researchers to engineer machines for the real world that possess at least some of the desirable properties of biological organisms, such as adaptivity, robustness, versatility, and agility. Collective behavior based on self-organization has been shown in group-living animals from insects to vertebrates.

These findings have stimulated engineers to investigate approaches for the coordination of autonomous multi-robot systems based on self-organization.

Individuals, natural or artificial, are perceived as equivalent, and the collective decision emerges from nonlinear feedbacks based on local interactions. Even when in the minority, robots can modulate the collective decision-making process and produce a global pattern not observed in their absence.

These results demonstrate the possibility of using intelligent autonomous devices to study and control self-organized behavioral patterns in group-living animals.

Self-organization is a central coordination mechanism exhibited by both natural and artificial collective systems. Self-organized mechanisms are characterized by nonlinear responses to stimulus intensity, incomplete information, and randomness. Self-organization coexists with guidance from environmental templates, networks of interactions among individuals, and various forms of leadership or preexisting individual specialization. Studies of animal societies show that self-organization is used to coordinate group members, to reach consensus, and to maintain social coherence when group members have to choose between mutually exclusive opportunities.

These biological findings have stimulated engineers to investigate novel approaches for the coordination of autonomous multi-robot systems. Swarm-robotic systems, in contrast with other multi-robot systems, explicitly exploit self-organization as a main coordination mechanism. Often, the controller of individual robots is designed using reactive, behavior-based techniques [9]: robots act and interact with their close environment, which sends immediate feedback to their receptors in response to their own actions and the actions of others. Behavior-based techniques allow for real-time implementation of the social nonlinear feedbacks influencing the whole system, minimization of onboard computational resources under tight volume constraints, and suitable support for the injection of stochastic behavioral rules. An important goal of collective robotics is the design of control systems that allow groups of robots to accomplish common tasks by coordinating without a centralized control.

In a swarm robotic system, although each single robot is fully autonomous, the swarm as a whole can solve problems that a single robot cannot cope with because of physical constraints or limited behavioral capabilities. Swarm robotics emphasizes aspects such as decentralization of control, local and simple communication among robots, emergence of global behavior, and robustness. Moreover, swarm robotics aims at exploiting self-organizing principles similar to those observed in social insects. swarm-bots combine the power of swarm intelligence, as they are based on the emergent collective intelligence of groups of robots, and the flexibility of self-reconfiguration as they might dynamically change their structure to match environmental variability [8] Although traditionally, biologically inspired (bio-inspired) robotics has been largely about neural modeling (for example, for phonotaxis, navigation, or vision), recent developments in the field have centered on the notions of self-organization and embodiment; that is, the reciprocal and dynamical coupling among brain (control), body, and environment. Most advances converge onto a set of principles that are implicitly or explicitly employed by robot designers [10].

First, the behavior of any system is not merely the outcome of an internal control structure (such as the central nervous system). A system's behavior is also affected by the ecological niche in which the system is physically embedded, by its morphology (the shape of its body and limbs, as well as the type and placement of sensors and effectors), and by the material properties of the elements composing the morphology.

Second, physical constraints shape the dynamics of the interaction of the embodied system with its environment (for example, because of the way it is attached to the body at the hip joint, during walking a leg behaves to some extent like a pendulum) and can be exploited to achieve stability, maneuverability, and energy efficiency.

Third, a direct link exists between embodiment and information: Coupled sensory-motor activity and body morphology induce statistical regularities in sensory input and within the control architecture and therefore enhance internal information processing.

Fourth, viewing an embodied agent as a complex dynamical system enables us to employ concepts such as self-organization and emergence rather than hierarchical top-down control.

As we review some of the recent advances in bio-inspired robotics, it will become clear that autonomous agents display self-organization and emergence at multiple levels: at the level of induction of sensory stimulation, movement generation, exploitation of morphological and material properties, and interaction between individual modules and entire agents.

2.1 Principles and Physical Model Examples of Self-Organization

The theory of self-organization, learning and adaptation has grown out of a variety of disciplines, including quantum mechanics, thermodynamics, cybernetics, control theory and computer modeling. The present section reviews its most important definitions, principles, model descriptions and engineering concepts that can be used in design of robust intelligent control systems.

A. *Definitions and main properties of self-organization.* Self-organization is defined in general form as following: *The spontaneous emergence of large-scale spatial, temporal, or spatiotemporal order in a system of locally interacting, relatively simple components.* Self-organization is a *bottom-up* process where complex organization emerges at multiple levels from the interaction of lower-level entities. The final product is the result of nonlinear interactions rather than planning and design, and is not known a priori. Contrast this with the standard, *top-down* engineering design paradigm where planning precedes implementation, and the desired final system is known by design. *Self-organization* can be defined as the spontaneous creation of a globally coherent pattern out of local interactions. Because of its distributed character, this organization tends to be *robust*, resisting perturbations. The dynamics of a self-organizing system is typically nonlinear, because of circular or feedback relations between the components. *Positive feedback* leads to an explosive growth, which ends when all components have been absorbed into the new configuration, leaving the system in a stable, *negative feedback* state. Nonlinear systems have in general several stable states, and this number tends to increase (bifurcate) as an increasing input of energy pushes the system farther from its thermodynamic equilibrium. To adapt to a changing environment, the system needs a variety of stable states that is large enough to react to all perturbations but not so large as to make its evolution uncontrollably chaotic. The most adequate states are selected according to their fitness, either directly by the environment, or by subsystems that have adapted to the environment at an earlier stage. Formally, the basic mechanism underlying self-organization is the (often noise-driven) variation which explores different regions in the system's state space until it enters an *attractor*. This precludes further variation outside the attractor, and thus restricts the freedom of the system's components to behave independently. This is equivalent to the increase of coherence, or *decrease* of statistical *entropy*, that defines *self-organization.* The most obvious change that has taken place in systems is the *emergence* of *global* organization. Initially the elements of the system (spins or molecules) were only interacting *locally.* This locality of interactions follows from the basic continuity of all physical processes: for any influence to pass from one region to another it must first pass through all intermediate regions.

In the self-organized state, on the other hand, all segments of the system are *strongly correlated.* This is most clear in the example of the magnet: in the magnetized state, all spins, however far apart, point in the same direction. *Correlation* is a useful measure to study the transition from the disordered to the ordered state. Locality implies that neighboring configurations are strongly correlated, but that this correlation diminishes as the distance between configurations increases. The *correlation length* can be defined as the maximum distance over which there is a significant correlation. When we consider a highly organized system, we usually imagine some external or internal agent (controller) that is responsible for guiding, directing or controlling that organization. The controller is a physically distinct subsystem that exerts its influence over the rest of the system. In this case, we may say that control is *centralized.* In self-organizing systems, on the other hand, "control" of the organization is typically *distributed* over the whole of the system. All parts contribute evenly to the resulting arrangement.

As mentioned in Introduction a general characteristic of self-organizing systems is as following: they are *robust* or *resilient*. This means that they are relatively insensitive to perturbations or errors, and have a strong capacity to restore themselves, unlike most human designed systems. *One reason* for this fault-tolerance is the *redundant*, *distributed* organization: the non-damaged regions can usually make up for the damaged ones. *Another reason* for this intrinsic robustness is that self-organization thrives on *randomness*, fluctuations or "noise". A certain amount of random perturbations will facilitate rather than hinder self-organization. A *third reason* for resilience is the stabilizing effect of *feedback* loops. Many self-organizational processes begin with the amplification (through positive feedback) of initial random fluctuations. This breaks the symmetry of the initial state, but often in unpredictable but operationally equivalent ways. That is, the job gets done, but hostile forces will have difficulty predicting precisely how it gets done.

B. *Principles of Self-Organization.* A system can cope with an unpredictable environment autonomously using different but closely related approaches:

— *Adaptation* (learning, evolution). The system changes its behavior to cope with the change.

— *Anticipation* (cognition). The system predicts a change to cope with, and adjusts its behavior accordingly. This is a special case of adaptation, where the system does not require experiencing a situation before responding to it.

— *Robustness.* A system is robust if it continues to function in the face of perturbations. This can be achieved with modularity, degeneracy, distributed robustness, or redundancy.

Successful self-organizing systems will use combinations of these approaches to maintain their integrity in a changing and unexpected environment. *Adaptation* will enable the system to modify itself to "fit" better within the environment. *Robustness* will allow the system to withstand changes without losing its function or purpose, and thus allowing it to adapt. *Anticipation* will prepare the system for changes before these occur, adapting the system without it being perturbed.

C. *Quantum control algorithm of self-organization processes.* Let us consider the peculiarities of common parts in self-organization models: (i) Models of self-organizations on macro-level use the information from micro-level that supports thermodynamic relations (second law of thermodynamics: increasing and decreasing of entropy on micro- and macro-levels, correspondingly) of dynamic evolution; (ii) Self-organization processes use transport of the information on/to macro- and from micro-levels in different hidden forms; (iii) Final states of self-organized structure have minimum of entropy production; (iv) In nature the self-organization processes don't plan types of correlation before the evolution (Nature given the type of corresponding correlation through genetic coding of templates in self-assembly); Coordination control for design of self-organization structure is used; Random searching process for self-organization structure design is applied; (vii) Natural models are biologically inspired evolution dynamic models and use current classical information for decision-making (but don't have toolkit for extraction and exchanging the hidden quantum information from dynamic behavior of control object).

In man-made processes the self-organization *types of correlations* and *control of self-organization* are developed before the design of the searching structure.

Thus the future design algorithm of self-organization must include these common peculiarities of bio-inspired and man-made processes: *quantum hidden correlations* and *information transport*.

Figure 3 shows the structure of a new *quantum control algorithm of self-organization* that includes the above mentioned properties.

Remark. The developed quantum control algorithm includes three possibilities: (i) from the simplest living organism composition in response to external stimuli of bacterial and neuronal self-organization; and (ii) according to correlation information stored in the DNA; (iii) from quantum hidden correlations and information transport used in quantum dots.

Quantum control algorithm of self-organization design in intelligent control systems based on QFI-model is described in [11]. Below we will describe the Level 1 (see, Fig. 3) based on QFI model as the background of robust KB design information technology.

QFI model is described in details in [7] and used here as toolkit.

Main goal of quantum control algorithm of self-organization in Fig. 3 is the support of optimal *thermodynamic trade-off* between *stability*, *controllability* and *robustness* of control object behavior using robust self-organized KB of intelligent control system.

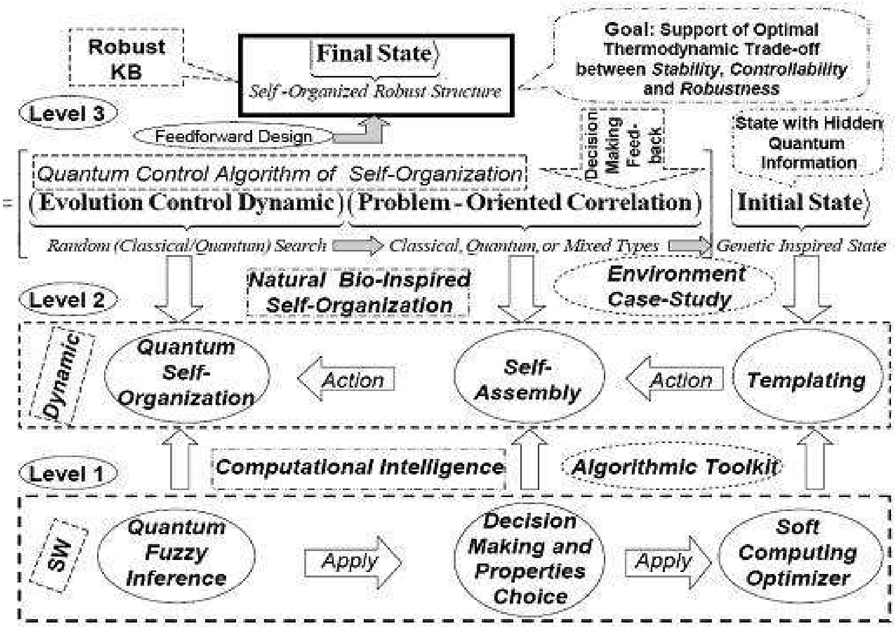


Figure 3. General structure of quantum control algorithm of self-organization

Q: *Why with thermodynamics approach we can organize trade-off between stability, controllability and robustness*?

Let us consider the answer on this question.

2.2 Thermodynamics trade-off between stability, controllability, and robustness

Consider a dynamic controlled plant given by the equation

$$\frac{dq}{dt} = \varphi\left(q, S\left(t\right), t, u, \xi\left(t\right)\right), \quad u = f\left(q, q_d, t\right), \tag{1}$$

where q is the vector of generalized coordinates describing the dynamics of the controlled plant; S is the generalized entropy of dynamic system (1); u is the control force (the output of the actuator of the automatic control system); $q_d\left(t\right)$ is reference signal, $\xi\left(t\right)$ is random disturbance and t is the time. The necessary and sufficient conditions of asymptotic stability of dynamic system (1) with $\xi\left(t\right) \equiv 0$ are determined by the physical constraints on the form of the Lyapunov function, which possesses two important properties represented by the following conditions: (I) This is a strictly positive function of generalized coordinates, i.e., $V > 0$; (II) The complete derivative in time of the Lyapunov's function is a non-positive function, $\frac{dV}{dt} \leq 0$.

In general case the Lagrangian dynamic system (1) is not lossless with corresponding outputs.

By conditions (I) and (II), as the generalized Lyapunov function, we take the function

$$V = \frac{1}{2}\sum_{i=1}^{n} q_i^2 + \frac{1}{2}S^2, \tag{2}$$

where $S = S_p - S_c$ is the production of entropy in the open system "*control object + controller*"; $S_p = \Psi\left(q, \dot{q}, t\right)$ is the production of entropy in the controlled plant; and $S_c = \Upsilon\left(\dot{e}, t\right)$ is the production of entropy in the controller (actuator of the automatic control system). It is possible to introduce the entropy characteristics in Eqs. (1) and (2) because of the scalar property of entropy as a function of time, $S\left(t\right)$.

Remark. It is worth noting that the presence of entropy production in (1) as a parameter (for example, entropy production term in dissipative process) reflects the dynamics of the behavior of the controlled plant and results in a new class of substantially nonlinear dynamic automatic control systems. The choice of the minimum entropy production both in the control object and in the fuzzy PID controller as a fitness function in the genetic algorithm allows one to obtain feasible robust control laws for the gains in the fuzzy PID controller. The entropy production of a dynamic system is characterized uniquely by the parameters of the nonlinear dynamic automatic control system, which results in determination of an optimal selective trajectory from the set of possible trajectories in optimization problems.

Thus, the first condition is fulfilled automatically. Assume that the second condition $\frac{dV}{dt} \leq 0$ holds. In this case, the complete derivative of the Lyapunov function (2) has the form

$$\frac{dV}{dt} = \sum_i q_i \dot{q}_i + S\dot{S} = \sum_i q_i \varphi_i \left(q, S, t, u\right) + \left(S_{cob} - S_c\right)\left(\dot{S}_{cob} - \dot{S}_c\right).$$

Taking into account (1) and the notation introduced above, we have

$$\underbrace{\frac{dV}{dt}}_{\text{Stability}} = \underbrace{\sum_i q_i \varphi_i \left(q, \left(\Psi - \Upsilon\right), t, u\right)}_{\text{Controllability}} + \underbrace{\left(\Psi - \Upsilon\right)\left(\dot{\Psi} - \dot{\Upsilon}\right)}_{\text{Robustness}} \leq 0. \quad (3)$$

Relation (3) relates the stability, controllability, and robustness properties.

Remark. It was introduced the new physical measure of control quality (3) to complex non-linear controlled objects described as non-linear dissipative models. This physical measure of control quality is based on the physical law of minimum entropy production rate in intelligent control system and in dynamic behavior of complex object. The problem of the minimum entropy production rate is *equivalent* with the associated problem of the maximum released mechanical work as the optimal solutions of corresponding Hamilton-Jacobi-Bellman equations. It has shown that the variational fixed-end problem of the *maximum work W* is equivalent to the variational fixed-end problem of the *minimum entropy production.* In this case both optimal solutions are equivalent for the dynamic control of complex systems, and the principle of minimum of entropy production guarantees the maximal released mechanical work with intelligent operations. This new physical measure of control quality we use as fitness function of GA in optimal control system design.

Such state corresponds to the minimum of system entropy. The introduction of physical criteria (the minimum entropy production rate) can guarantee the stability and robustness of control. This method differs from aforesaid design method in that a new *intelligent global feedback* in control system is introduced. The interrelation between the stability of control object (the Lyapunov function) and controllability (the entropy production rate) is used. The basic peculiarity of the given method is the necessity of model investigation for control object and the calculation of entropy production rate through the parameters of the developed model. The integration of joint systems of equations (the equations of mechanical model motion and the equations of entropy production rate) enable to use the result as the fitness function in GA.

Remark. The concept of an energy-based hybrid controller [12] can be viewed from (3) also as a feedback control technique that exploits the coupling between a physical dynamical system and an energy-based controller to efficiently remove energy from the physical system. According to (3) we have

$$\sum_i q_i \varphi_i \left(q, (\Psi - \Upsilon), t, u\right) + (\Psi - \Upsilon)\left(\dot{\Psi} - \dot{\Upsilon}\right) \le 0,$$

or

$$\sum_i q_i \varphi_i \left(q, (\Psi - \Upsilon), t, u\right) \le (\Psi - \Upsilon)\left(\dot{\Upsilon} - \dot{\Psi}\right). \tag{4}$$

Therefore, we have different possibilities for support inequalities in (4) as following:

$$\text{(i)} \sum_i q_i \dot{q}_i < 0,\ (\Psi > \Upsilon),\left(\dot{\Upsilon} > \dot{\Psi}\right),\ S\dot{S} > 0;$$
$$\text{(ii)} \sum_i q_i \dot{q}_i < 0,\ (\Psi < \Upsilon),\left(\dot{\Upsilon} < \dot{\Psi}\right),\ S\dot{S} > 0;$$

(iii)$\sum_i q_i \dot{q}_i < 0,\ (\Psi < \Upsilon)\,;\left(\dot{\Upsilon} > \dot{\Psi}\right),\ S\dot{S} < 0,\ \sum_i q_i \dot{q}_i < S\dot{S}$, etc

and its combinations, that means thermodynamically stabilizing compensator can be constructed. These inequalities, specifically if a dissipative or lossless plant is at high energy level, and a lossless feedback controller at a low energy level, are attached to it, then energy will generally tend to flow from the plant into the controller, decreasing the plant energy and increasing the controller energy. Emulated energy, and not physical energy are accumulated by the controller. Conversely, if the attached controller is at a high energy level and a plant is at a low energy level, then energy can flow from the controller to the plant, since a controller can generate real, physical energy to effect the required energy flow. Hence, if and when the controller states coincide with a high emulated energy level, then it is possible reset these states to remove the emulated energy so that the emulated energy is not returned to the plant. In this case, the overall closed-loop system consisting of the plant and the controller possesses discontinuous flows since it combines logical switching with continuous dynamics, leading to impulsive differential equations.

Every time the emulated energy of the controller reaches its maximum, the states of the controller reset in such a way that the controller's emulated energy becomes zero. Alternatively, the controller states can be made reset every time the emulated energy is equal to the actual energy of the plant, enforcing the second law of thermodynamics that ensures that the energy flows from the more energetic system (the plant) to the less energetic system (the controller). The proof of asymptotic stability of the closed-loop system in this case requires the non-trivial extension of the hybrid invariance principle, which in turn is a very recent extension of the classical *Barbashin-Krasovskii* invariant set theorem. The subtlety here is that the resetting set is not a closed set and as such a new transversality condition involving higher-order Lie derivatives is needed.

Main goal of robust intelligent control is support of optimal *trade-off* between stability, controllability and robustness with thermodynamic relation as (3) or (4) as thermodynamically stabilizing compensator.

The resetting set is thus defined to be the set of all points in the closed-loop state space that correspond to decreasing controller emulated energy. By resetting the controller states, the plant energy can never increase after the first resetting event. Furthermore, if the closed-loop system total energy is conserved between resetting events, then a decrease in plant energy is accompanied by a corresponding increase in emulated energy. Hence, this approach allows the plant energy to flow to the controller, where it increases the emulated energy but does not allow the emulated energy to flow back to the plant after the first resetting event.

This energy dissipating hybrid controller effectively enforces a one-way energy transfer between the plant and the controller after the first resetting event. For practical implementation, knowledge of controller and object outputs is sufficient to determine whether or not the closed-loop state vector is in the resetting set. Since the energy-based hybrid controller architecture involves the exchange of energy with conservation laws describing transfer, accumulation, and dissipation of energy between the controller and the plant, we can construct a modified hybrid controller that guarantees that the closed-loop system is consistent with basic thermodynamic principles after the first resetting event. The entropy of the closed-loop system strictly increases between resetting events after the first resetting event, which is consistent with thermodynamic principles. This is not surprising since in this case the closed-loop system is *adiabatically isolated* (i.e., the system does not exchange energy (heat) with the environment) and the total energy of the closed-loop system is conserved between resetting events. Alternatively, the entropy of the closed-loop system strictly decreases across resetting events since the total energy strictly decreases at each resetting instant, and hence, energy is not conserved across resetting events.

Entropy production rate is a continuously differentiable function that defines the resetting set as its zero level set. Thus the resetting set is motivated by thermodynamic principles and guarantees that the energy of the closed-loop system is always flowing from regions of higher to lower energies after the first resetting event, which is in accordance with the second law of thermodynamics. This guarantees the existence of entropy function for the closed-loop system that satisfies the Clausius-type inequality between resetting events. Hence, it resets the compensator states in order to ensure that the second law of thermodynamics is not violated. Furthermore, in this case, the hybrid controller with resetting set is a thermodynamically stabilizing compensator. Analogous thermodynamically stabilizing compensators can be constructed for lossless dynamical systems.

Eq. (3) joints in analytic form different measures of control quality such as *stability, controllability*, and *robustness* supporting the required level of reliability and accuracy. As particular case Eq. (3) includes the entropic principle of robustness. Consequently, the interrelation between the Lyapunov stability and robustness described by Eq. (3) is the main physical law for designing automatic control systems.

This law provides the background for an applied technique of designing KBs of robust intelligent control systems (with different levels of intelligence) with the use of soft computing.

To complete this section, we formulate the following conclusions:

1. The introduced physical law of intelligent control (3) provides a background of design of robust knowledge bases of intelligent control systems (with different levels of intelligence) based on soft computing.

2. The technique of soft computing gives the opportunity to develop a universal approximator in the form of a fuzzy automatic control system, which elicits information from the data of simulation of the dynamic behavior of the controlled plant and the actuator of the automatic control system.

3. The application of soft computing guarantees the purposeful design of the corresponding robustness level by an optimal design of the total number of production rules and types of membership functions in the knowledge base.

The main components and their interrelations in the information design technology (IDT) are based on new types of (soft and quantum) computing. The key point of this IDT is the use of the method of eliciting objective knowledge about the control process irrespective of the subjective experience of experts and the design of objective knowledge bases of a fuzzy controller (FC), which is principal component of a robust intelligent control system. The output result of application of this IDT is a robust knowledge base of the FC that allows the intelligent control system to operate under various types of information uncertainty.

Self-organized intelligent control system based on soft computing technology can support thermodynamic trade-off in interrelations between stability, controllability and robustness.

Remark. Unfortunately, soft computing approach also has bounded possibilities for global optimization while multi-objective GA can work on fixed space of searched solutions. It means that robustness of control can be guaranteed on similar unpredicted control situations. The choice of search space in GA is depended on the knowledge base of expert. It means that there exists the possibility that the searched solution is not included into the search space. (It is very difficult to find black cat in dark room if you know that the cat is absent in this room.) The support of optimal *thermodynamic trade-off* between *stability*, *controllability* and *robustness* in self-organization processes (see, Fig. 3) with (3) or (4) can be realized using a new quantum control algorithm of self-organization in KB of robust FC based on quantum computing operations (that are absent in soft computing toolkit).

Let us consider the main self-organization idea and the corresponding structure of quantum control algorithm as QFI that can realize the self-organization process.

3 Quantum intelligent IT design of IFICS

The information design technology of robust integrated fuzzy intelligent control systems (IFICS) is presented in Fig. 4.

Main problem in this technology is the design of robust knowledge bases (KB) of FC that can include the self-organization of knowledge in unpredicted control situations. The background of this design processes is KB optimizer based on quantum/soft computing. Concrete industrial Benchmarks (as 'cart - pole' system, robotic unicycle, robotic motorcycle, mobile robot for service use, semi-active car suspension system etc.) are tested successfully with the developed design technology. The role of Kansei engineering in System of System Engineering is demonstrated.

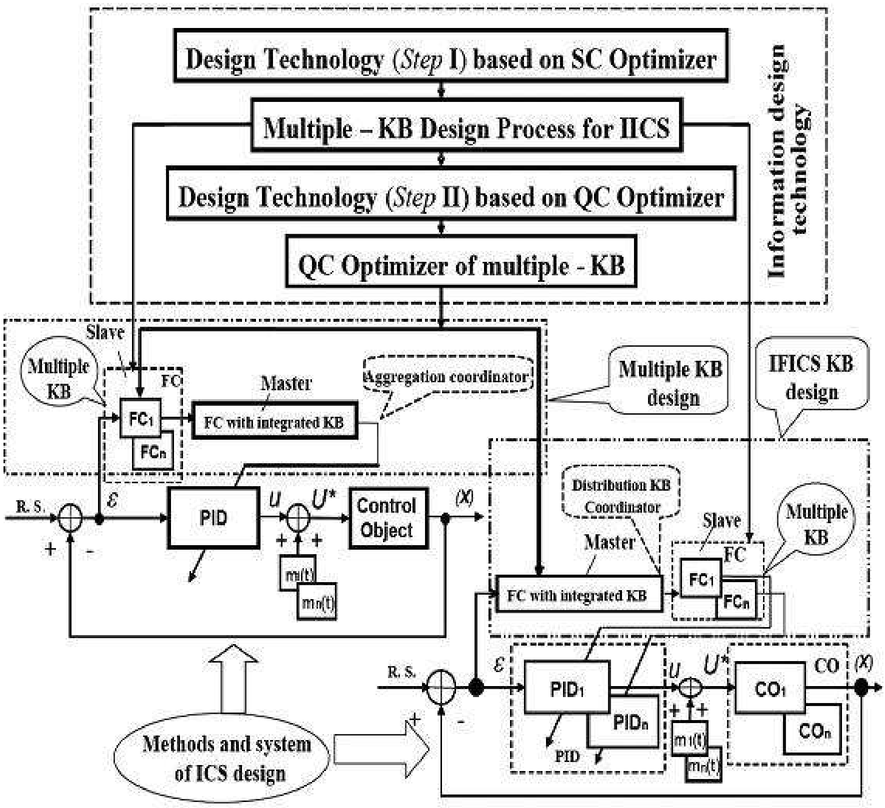


Figure 4. Structure of information design technology of IFICS

3.1 Unconventional computational intelligence: Soft and quantum computing technologies

Soft computing and quantum computing are new types of unconventional computational intelligence (details see in http://www.qcoptimizer.com/). Technology of soft computing is based on genetic algorithm, fuzzy neural network, and fuzzy logic inference. Quantum computational intelligence uses quantum search algorithm, quantum neural network, and quantum fuzzy inference.

These algorithms include three main operators. In genetic algorithm selection, crossover, and mutation operators are used. In quantum search algorithm superposition, entanglement, and interference are used.

An application of developed toolkit in design of "*Hu-Machine* technology" based on Kansei Engineering is demonstrated for emotion generating enterprise (purpose of enterprise).

3.2 Kansei Engineering and robust IFICS design

We considered the humanized technology of intelligent robotic systems design based on Kansei Engineering and Quantum/Soft Computing. As well known the subject of humanized technology or human-related systems has been actively researched. With the increasing concern regarding human factors in system development Kansei Engineering and Soft Computing are the most representative research fields on this subject. Soft computing toolkit is developed for emotion, instinct, and intuition recognition and expression generation. In particular, with genetic algorithm (as effective random search of solution) an intuition process is modeled. Fuzzy neural network is used for description of instinct process that modeled approximation of optimal solution in unpredicted control situation. Fuzzy logic control is used for design of emotion according to corresponding look-up table. Quantum computing toolkit is used for increasing of robustness in intelligent control systems based on superposition and correlations of affective operations.

4 Examples of solutions

The structure of robust intelligent control system in unpredicted control situations is shown in Fig. 5.

This structure is the particular case of general structure of IFICS (see Fig. 4).

Graphical interface of Quantum Fuzzy Inference (QFI) is shown in Fig. 6.

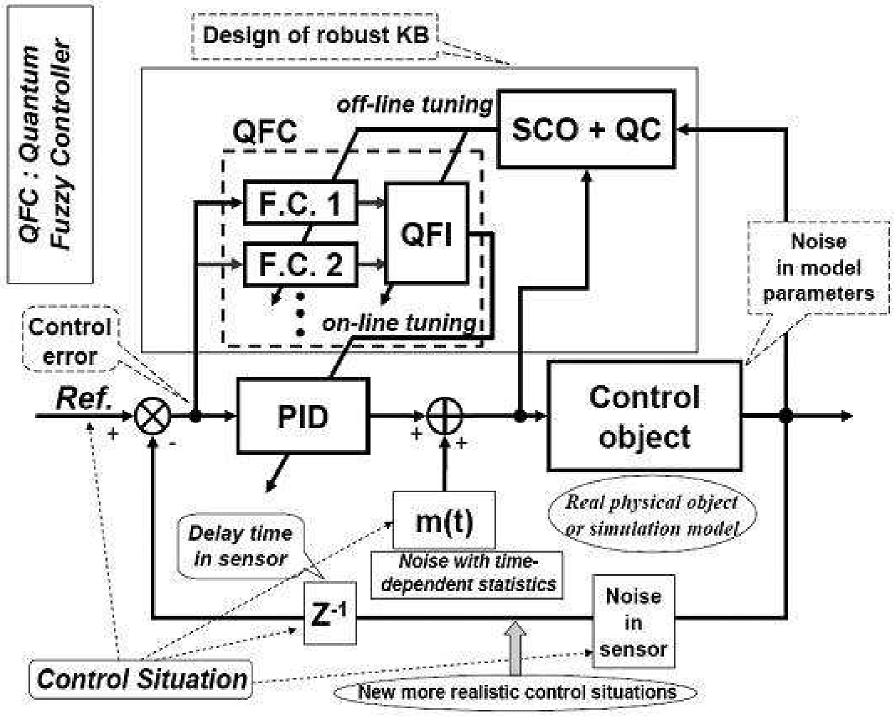


Figure 5. Structure of robust intelligent control system in unpredicted control situations

Detail description of graphical interface and quantum fuzzy inference are described in [7].

Concrete Benchmark is described in details with the application of intelligent control system in Fig. 5 as following.

4.1 Benchmark of QFI-application: "Cart-pole" system

Let us consider fuzzy control problem of "Cart-pole" system as intelligent control Benchmark. This system is described by the following equation of motion:

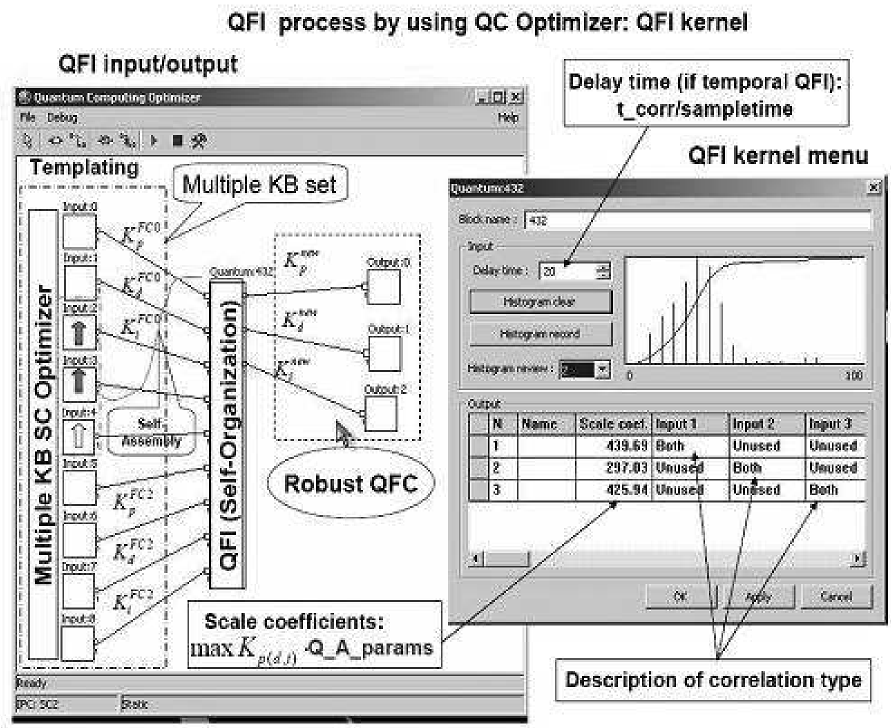


Figure 6. Interface structure of SW quantum fuzzy inference

$$\ddot{\theta} = \frac{g\sin\theta + \cos\theta\left(\frac{(u+\xi(t))+\{a_1\dot{z}+a_2z\}-ml\dot{\theta}^2\sin\theta}{M+m}\right) - k\dot{\theta}}{l\left(\frac{4}{3} - \frac{m\cos^2\theta}{M+m}\right)}$$

$$\ddot{z} = \frac{u+\xi(t)+-\{a_1\dot{z}+a_2z\}+m\ell\left(\dot{\theta}^2\sin\theta - \ddot{\theta}\cos\theta\right)}{M+m}, \qquad (5)$$

where θ and z are generalized coordinates (angle of pole and position of cart, correspondingly); $u\,(t)$ is control force; and $\xi\,(t)$ is random excitation.

Knowledge base of FC(1,2) is designed with Soft Computing Optimizer using Gaussian and Raleigh noises correspondingly.

Figure 7 shows the dynamic behavior of the system (5) in unpredicted control situation.

In this case a new time delay in the structure (see Fig. 5) in sensor is 0.002 sec; parametric Gaussian noise is with the amplitude 0.01; new initial state $\left[\theta_0, \dot{\theta}_0\right] = [13, 1] \ \ (\text{deg})\,,\ [z_0, \dot{z}_0] = [0, 0]$.

External noise is Raleigh noise as in the learning situation.

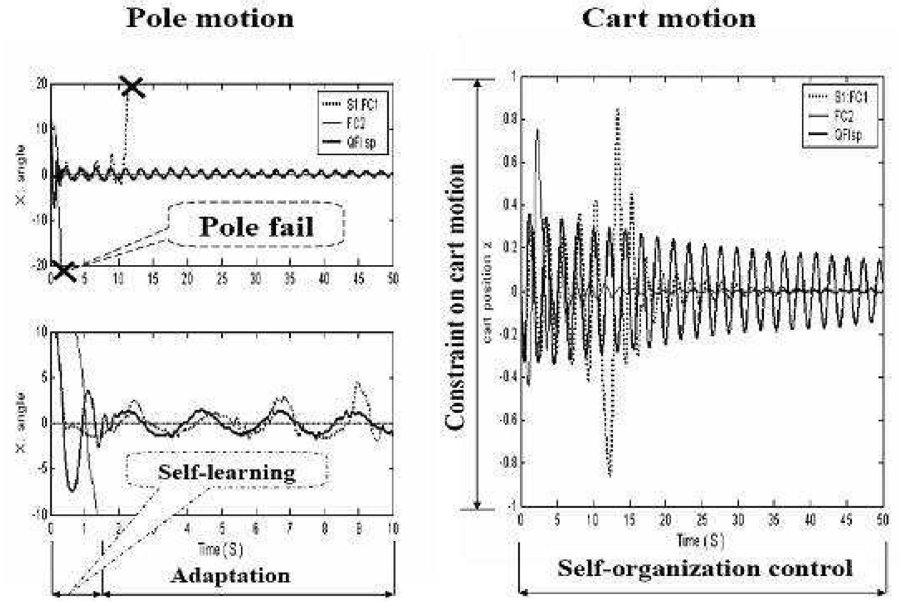


Figure 7. Dynamic behavior of "cart-pole" system

Figure 8 shows the thermodynamic behavior of the system (5) and of fuzzy controller.

Results of simulations show that from two unstable fuzzy controllers it is possible to design a new robust fuzzy controller on-line. It is a pure quantum effect and has no classical analogy.

Figure 8 shows that generalized entropy production of the system "control object + fuzzy PID-controller" is minimal and with quantum self-organization of knowledge base required trade-off distribution between stability, controllability and robustness is achieved (see Fig. 3).

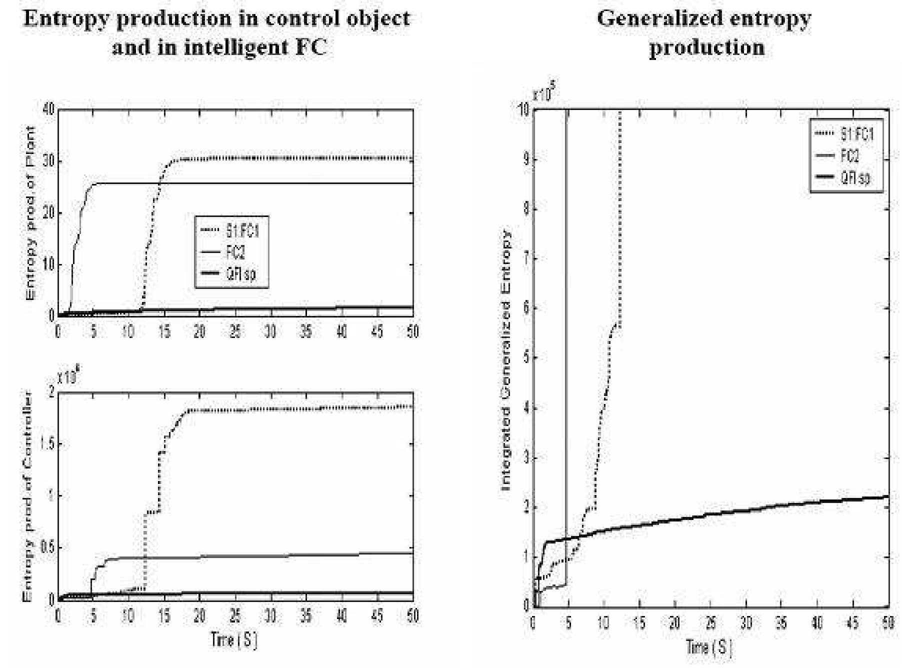


Figure 8. Dynamic behavior of "cart-pole" system

Thus, results of simulation show that winner is quantum fuzzy controller (QFC) designed from two KB controllers with minimum of generalized entropy production. Therefore, QFI supports optimal *thermodynamic trade-off* between stability, controllability and robustness in self-organization process (from viewpoint of physical background of global robustness in intelligent control systems).

Also the following new result for advanced control system theory is important: controllers (FC1, FC2) are failed but QFC is designed with increasing robustness.

This approach was applied to other complex robotic systems.

4.2 Robotic unicycle

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. We developed a new biomechanical model with two closed link mechanisms and one turntable to emulate a human riding a unicycle by a robot. This study of rider's postural stability control on a unicycle began from the observation of a human riding on a unicycle with vestibular model as intelligent biomechanical model including instinct and intuition mechanisms.

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 is used for the investigation of an optimal control process and for the estimation of an artificial life of mobile robots [13].

A new physical measure (the minimum entropy production) for the description of the intelligent dynamic behavior and thermodynamic stability condition of a biomechanical model 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 according to the model representation results of [14]. Computer simulations in this study are carried out by the usage of *thermodynamic* equations for the motion 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.

Figures 9 and 10 demonstrate the unicycle model and results of simulations.

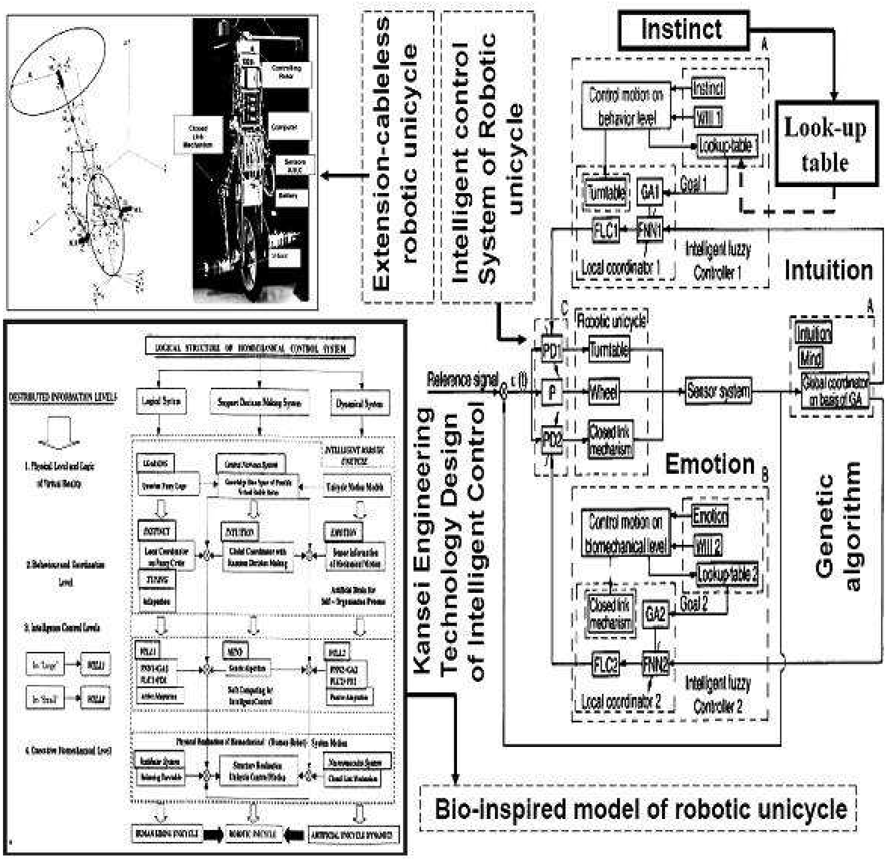


Figure 9. Robotic unicycle model

In particular, Fig. 9 shows the main idea of robotic unicycle design using Kansei and System of System Engineering approaches. With genetic algorithm the intuition of solution search is developed based on bio-inspired model of unicycle rider behavior. Instinct and emotion are introduced based on fuzzy neural network and corresponding look-up tables. Simulation and experimental results are demonstrated in Fig. 10.

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. 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.

Thus 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 report 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. Described above interrelation (3) between Lyapunov function (stability condition) and entropy

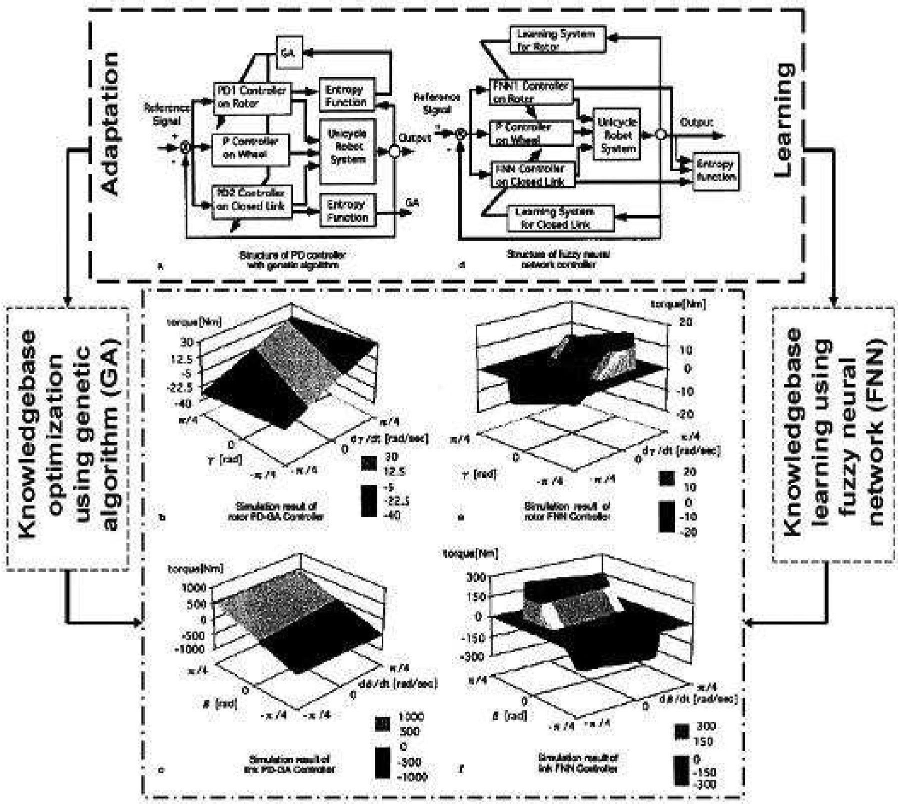


Figure 10. Simulation of robotic unicycle model

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 [15] of non-linear mechatronics and intelligent smart control.

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 based on a new physical concept of robust control, the minimum entropy production in control systems and in control object motion in general.

4.3 Mobile robot for service use

The mobile robot for service use works in buildings with different scenes of rooms and moves in unstructured environments in presence of many people and unexpected obstacles. We propose to construct a simulation system for mobile service robot behavior based on cognitive graphics. This system is used for possible world's simulation in the robot artificial life. This allows us to evaluate the control algorithms of real time robot behavior and to reduce difficulties connected with such troubles as robot collisions with obstacles and robot hardware damages. In this Item we describe a new approach to intelligent control system design using soft computing. A new form of direct human-robot communications (including emotion, instinct and intuition) and an autonomous locomotion control system were developed (see Fig. 11).

We considered as the first step one line in this scheme: direct human-robot communications based on natural language (NL) and construct the simulation system of spatial scenes and robot behavior in virtual reality (VR). We explained also the managing system which controls cooperatively three sub-systems of the service robot, as the locomotion system, the handling system for a mobile manipulator and the image processing system as human vision system. This managing system is based on GA and HN map method.

Meanwhile, three sub-systems which organize the service robot system for its autonomous navigation (see Fig. 11) and these soft computing are described. The locomotion control system is composed of four functions, i.e. locomotion control, planning for works, learning and recognition.

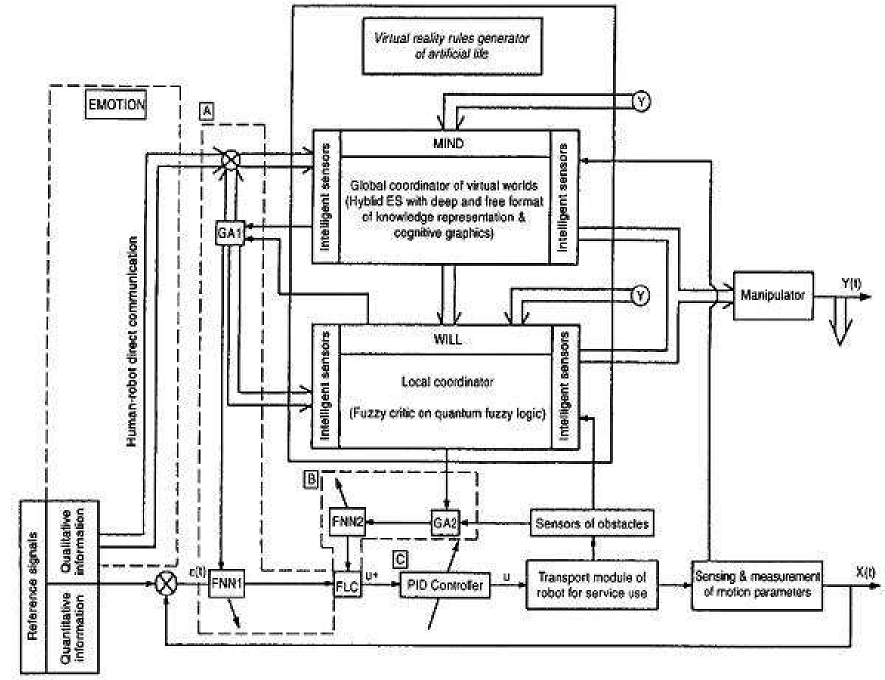


Figure 11. Structure of AI control system with distributed knowledge representation (on control signal levels). ***a*** – Intelligent control "in large"; ***b*** – Intelligent control "in small"; ***c*** – Control on executive level.

These four functions are related to each other. By using the handling system for a mobile manipulator and the image processing system as human vision system, the robot can realize some technology operations, for example, opening a door and getting on an elevator.

These three sub-systems are based on fuzzy control, FNN and GA.

Experimental results on the developed robot show that the proposed methods are very useful for autonomous locomotion control of the robot.

In this part we consider the use of natural language and cognitive graphics for condition descriptions of robot artificial life and direct human-robot communications for a mobile service robot shown in Fig. 12.

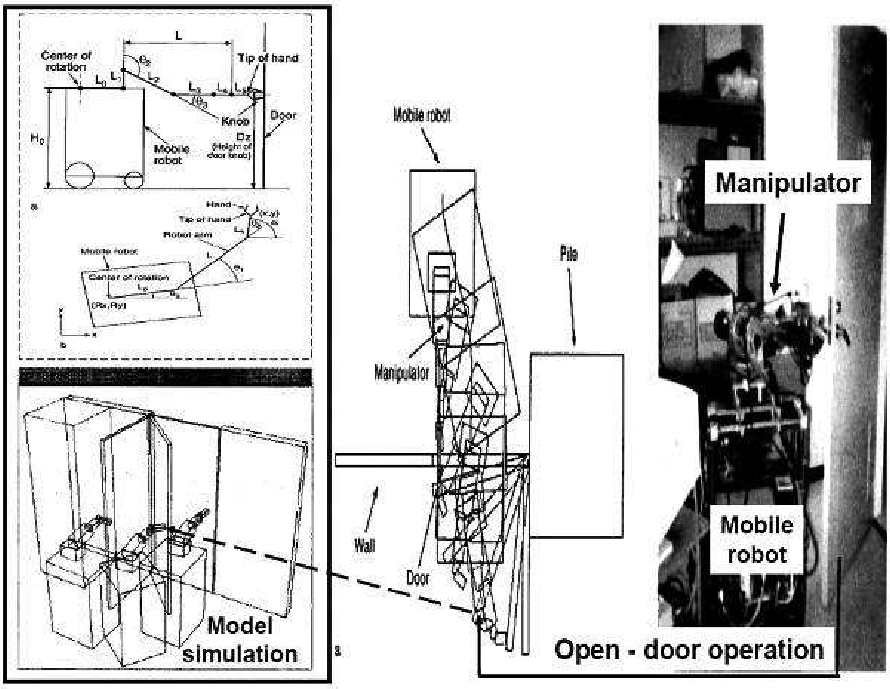


Figure 12. Mobile robot for service use

Example: *Intelligent control and soft computing for avoidance of obstacles and execution of technology operations.* This robot is power-wheeled steering type which is achieved by two driving wheels and a caster with passive suspension for stable locomotion. Thirteen ultrasonic (US) sensors, nine infrared (IR) sensors, a five degree-of-freedom (DOF) manipulator with a three finger hand and a CCD camera are equipped on the robot for conducting tasks and works in buildings including human being, opening door and getting on an elevator (see Fig. 13).

In the process of robot's locomotion in a building (See Fig. 13) from point to point the mobile robot must avoid obstacles in Room, and reach starting position for successful opening the room door (as technology operation from one point to another point) and go out of the Room to Elevator in presence of obstacles in a corridor. We discuss in detail this process as recognition of position and obstacles together with an intelligent control in navigation system. The above command or process is planned by the managing system which was described in [16].

Technological operation's design of robot for service use is a new Benchmark [17] of human-machine interaction and of evolutionary intelligent computing in non-linear mechatronics and intelligent smart control.

Other examples in [18 – 22] are described.

5 Conclusions

1. Applications of SW-support as Quantum Fuzzy Modeling System (QFMS) toolkit in design of robust integrated fuzzy intelligent control system (IFICS) in unpredicted control situations are discussed.
2. QFI supports the self-organization process in design technology of robust KB with optimal *thermodynamic trade-off* between stability, controllability and robustness in self-organization process.
3. Structure of SW-support as QFI tool is described.
4. Effectiveness of QMS is demonstrated with Benchmark simulation results. Application of QFI to design of robust KB in fuzzy PID-controller is demonstrated on example of robust behavior design in local and global unstable non-linear control objects.
5. Quantum fuzzy controller (QFC) based on QFI demonstrates the increasing robustness in complex unpredicted control situations. In this case *robust* QFC is designed from two (or three) fuzzy controllers that are *non-robust* in unpredicted control situation.

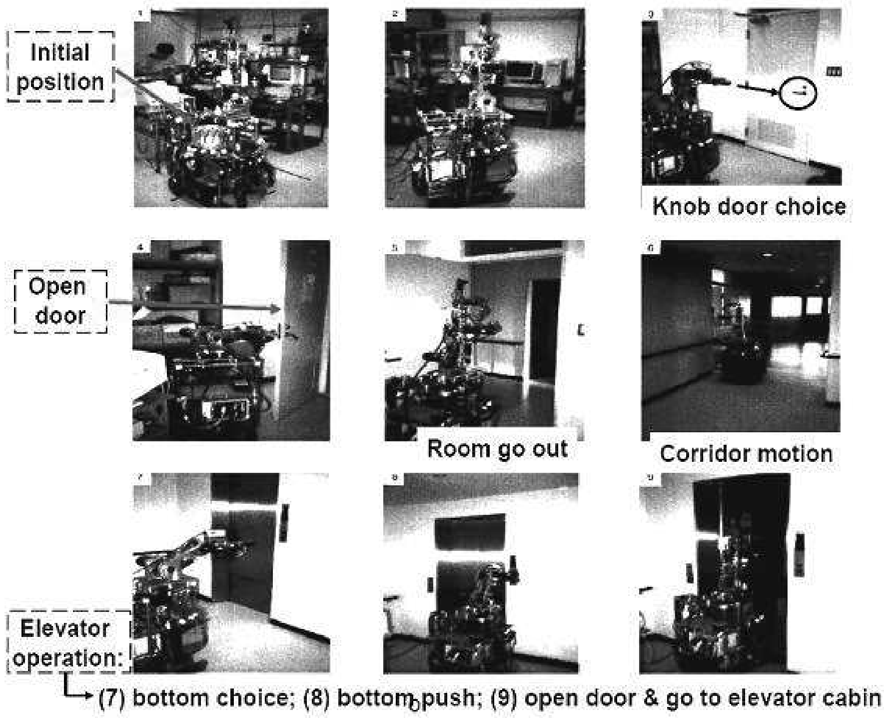


Figure 13. Navigation of mobile robot for service use

6. New design effect in advanced control theory and design technology of intelligent control system based on Kansei Engineering is demonstrated.

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Received August 23, 2013

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