

## INTELLIGENT SELF-ORGANIZED COGNITIVE CONTROLLERS. PT 1: KANSEI / AFFECTIVE ENGINEERING AND QUANTUM / SOFT COMPUTING TECHNOLOGIES

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

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

## ИНТЕЛЛЕКТУАЛЬНЫЕ САМООРГАНИЗУЮЩИЕСЯ КОГНИТИВНЫЕ РЕГУЛЯТОРЫ. Ч. 1: KANSEI / AFFECTIVE ИНЖЕНЕРИЯ И КВАНТОВЫЕ МЯГКИЕ ВЫЧИСЛЕНИЯ

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*Технология Kansei / Affective инженерии и инструментарий когнитивных вычислений содержит качественное описание эмоций, инстинкта и интуиции человека-оператора и применяется эффективно в интеллектуальной робототехнике и мехатронике. Технология системной инженерии описывает модели проектирования слабо структурированных объектов управления и включает в себя модели принятия решений в непредвиденных (нештатных) ситуациях управления с учетом человеческого фактора. В статье описывается возможность объединения технологий проектирования когнитивных регуляторов на основе технологий интеллектуальных вычислений. Основу интеллектуальных вычислений составляют мягкие и квантовые вычисления. Решение важной задачи проектирования робастных интеллектуальных систем управления основано на квантовой самоорганизации баз знаний в непредвиденных ситуациях и информационного риска. Применение разработанной технологии проектирования интегрированных нечетких интеллектуальных систем управления когнитивными роботами рассмотрено на конкретных примерах.*

**Ключевые слова:** Kansei / Affective инженерия, системная инженерия, интеллектуальный робот, эмоции, инстинкт, интуиция, мягкие вычисления, квантовые вычисления.

## 1. Introduction

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 [1, 2]. As well known the subject of humanized technology or human-related systems actively researched. Kansei / Affective Engineering technology and its cognitive toolkit include qualitative description of human being emotion, instinct and intuition that used effectively in design processes of smart / wise robotics and intelligent mechatronics.

According to general definition Kansei Engineering (Japanese: 感性工学 *kansei kougaku*, emotional / affective engineering) aims at the development or improvement of products and services by translating the customer's psychological feelings and needs into the domain of product design (i.e. parameters). It was founded by Mitsuo Nagamachi, Ph.D, Professor Emeritus of Hiroshima University. Kansei Engineering parametrically links the customer's emotional responses (i.e. physical and psychological) to the properties and characteristics of a product or service. In consequence, products can be designed to bring forward the intended feeling.

System of systems engineering technology describes the possibility of ill-defined (autonomous or hierarchically connected) dynamic control system's design that includes human decision making in unpredicted (unforeseen) control situations. The way how these technologies can be married using new types of unconventional computational intelligence is described.

With the increasing concern regarding human factors in system development Kansei Engineering [3 – 7] and Soft Computing are the most representative research fields on this subject [8]. Soft computing toolkit developed for emotion, instinct, and intuition recognition and expression generation [5 – 7, 9, 10]. In particular, with genetic algorithm – GA – (as effective random search of solution) an intuition process (optimization) modeled. Fuzzy neural network (FNN) used for description of instinct process (adaptation and learning) that modeled approximation of optimal solution in unpredicted control situation. Fuzzy logic control used for design of an emotion according to corresponding designed look-up table [9, 11]. Quantum control algorithm of self-organization is the background of wise robotic control system's design. Quantum computing toolkit is used for increasing of robustness in intelligent control systems (especially for unpredicted control situations) [12 – 15].

Figure 1 demonstrates the main approach and the creation of quantum intelligent design IT.

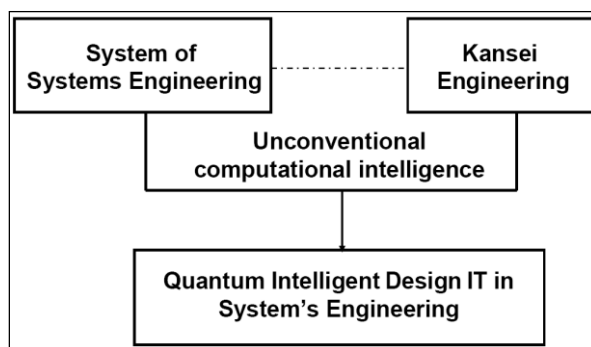


Figure 1. Structure background of quantum intelligent design IT

Let us consider the main definitions of Kansei / Affective engineering.

### 1.1. Kansei / Affective engineering

In Japan, the terminology of *Kansei* draws back on the German philosopher, Baumgarten. His work *AESTHETICA* (1750) was the first study that influenced *Kansei* engineering. The aim of *Kansei* study is to seek the structure of emotions which exists beneath human behaviors. This structure is referred to as a person's *Kansei*. In design practice, the designer has to balance between objective and subjective properties, between functional technology and emotional expressiveness, between information and inspiration. Lee showed the etymology of the term *Kansei* and compared it to another word: *Chisei* (Lee 2002) as following:

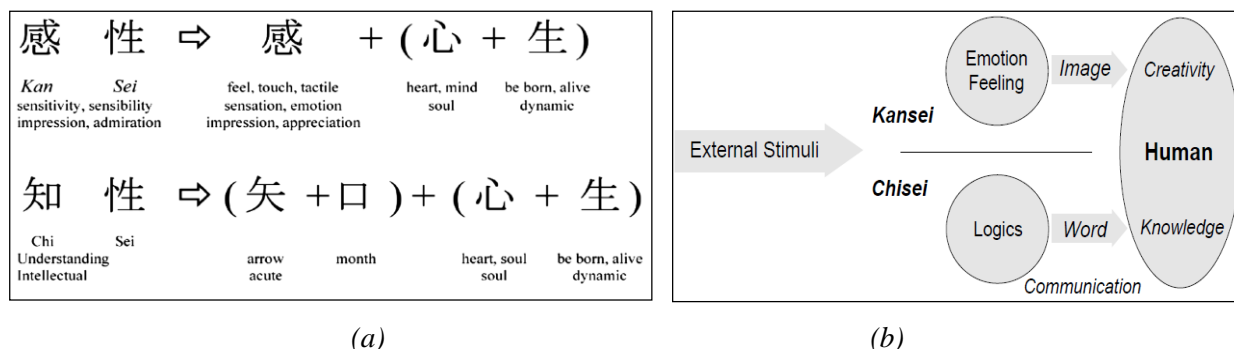


Figure 2. The Etymology of Kansei (a) and The effect of Kansei and Chisei (b)

Figure 2a shows the etymology of *Kansei* and *Chisei* interpreted from Chinese characters, both of which are processed in human minds when they receive the information from the external world. 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) [3]. *Kansei* has an effect to create more various feelings in the human mind which appear as individualized emotions. The functional requirements can often be solved by *Chisei*, logical knowledge of technology as in Fig. 2b. But the fulfilling of emotional requirements, including pleasure, requires attention for *Kansei*. Regarding those changes, we need to know the structure of *Kansei* and how to apply it to product design.

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 [3 – 7]:

- *Kansei* process gathers the functions related to emotions, sensitivity, feelings, experience, intuition (i.e. sensory qualities related functions (Clark 1996)), including inter actions 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 3a intends to describe the *Kansei* process [3].

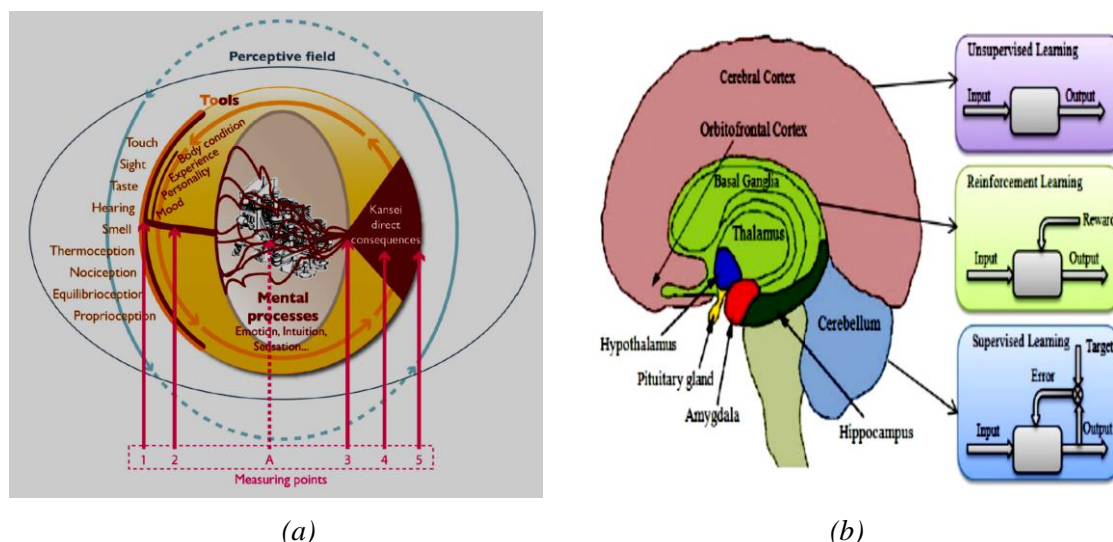


Figure 3. Comprehensive view on *Kansei* (a) and brain / cognitive controller's structures (b) [16]

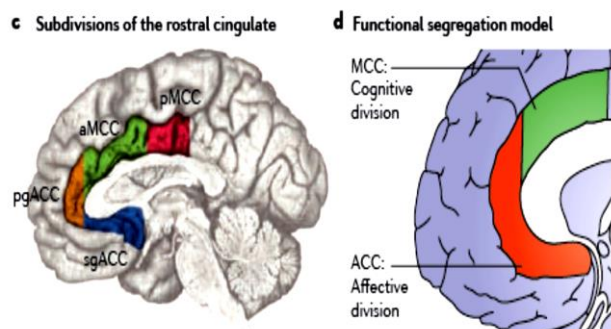
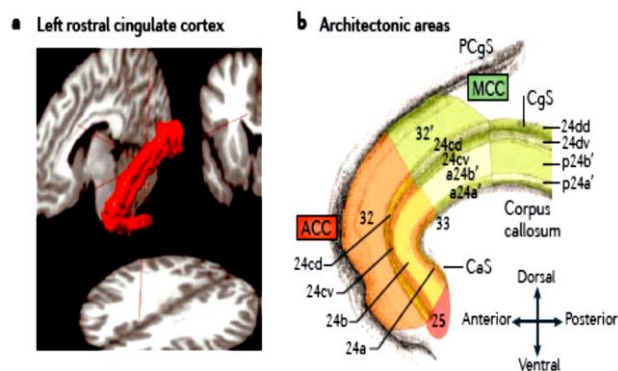
For a human, as a biological intelligent system, there are evidently many different areas in the brain where learning occurs. Figure 3b shows the relevant picture of the areas representing the three kinds of learning mechanisms in the human brain. The main part the mammalian brain which is responsible for emotional processes is called the limbic system. The computational models of the amygdala and orbitofrontal cortex which are the main parts of the limbic system were recently introduced for the first time. Therefore, *Kansei* result is a synthesis of sensory brain cognitive qualities. For example, it has argued that emotion, pain and cognitive control functionally segregated in distinct subdivisions of the cingulate cortex of brain.

However, recent observations encourage a fundamentally different view.

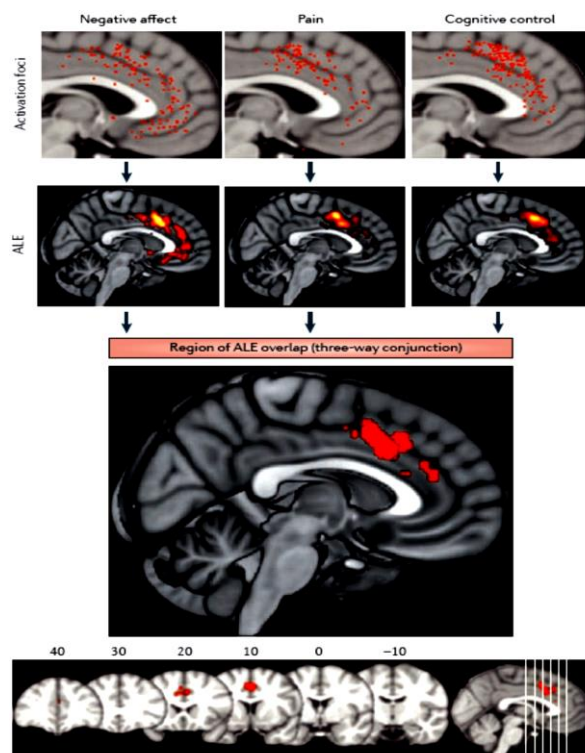
## 1.2. Contemporary models of affect, motivation, emotion and cognitive control for *Kansei* Engineering

Let us briefly consider the models of negative affect, pain and emotion that play important role in *Kansei* engineering and cognitive control.

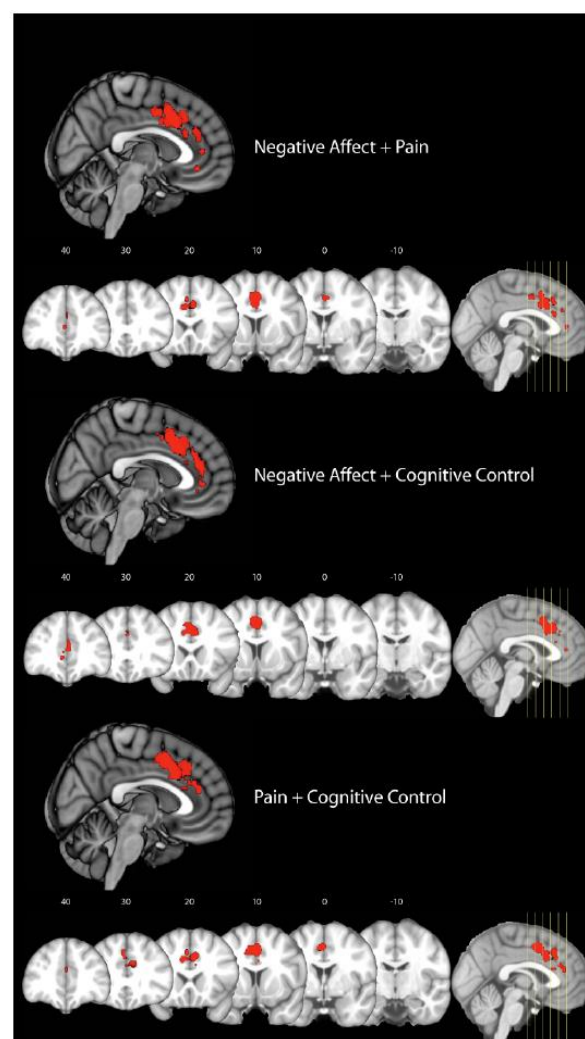
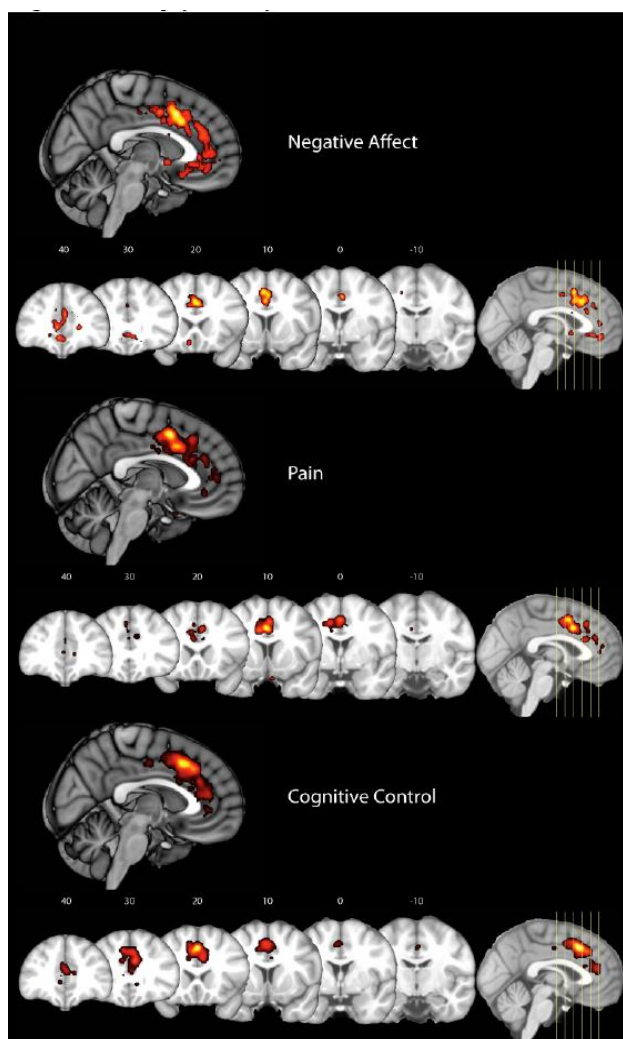
Example 1. In humans and other primates, the cingulate – a thick belt of cortex encircling the corpus callosum – is one of the most prominent features on the mesial surface of the brain (Fig. 4a). Early research suggested that the rostral cingulate cortex (Brodmann's 'precingulate'; architectonic areas) plays a key part in affect and motivation (Fig. 4b). More recent research has enlarged the breadth of functions ascribed to this region; in addition to emotion, the rostral cingulate cortex has a central role in contemporary models of pain and cognitive control. The most basic question is whether emotion, pain and cognitive control are segregated into distinct subdivisions of the rostral cingulate or are instead integrated in a common region. There is a growing recognition that aMCC might implement a domain-general process that is integral to negative affect, pain and cognitive control [17].



(a)

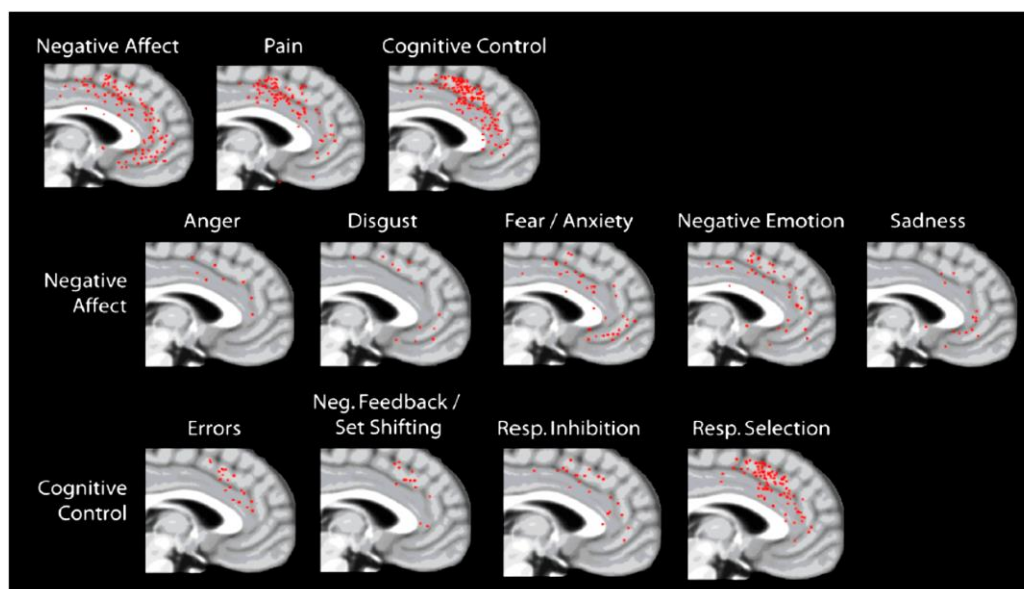


(b)



(c)





(d)

Figure 4. (a) – Divisions of the human rostral cingulate cortex; (b) – Negative affect, pain and cognitive control activate a common region within the anterior subdivision of the midcingulate cortex - aMCC (The map depicts the results of a coordinate-based meta-analysis (CBMA) of 380 activation foci derived from 192 experiments and involving more than 3,000 participants); (c) – Activation likelihood estimate (ALE) maps of the three behavioral domains (left) and pairwise ALE minimum conjunction maps; (d) – Activation foci maps [17]

Cognitive control is a range of elementary processes (such as attention, inhibition and learning) that are engaged when automatic or habitual responses are insufficient to sustain goal-directed behavior. Control can be engaged proactively or reactively. Activation foci maps between negative affect, pain and cognitive control is shown on Fig. 4d.

Example 2. Human being hands are not only suitable for manipulating objects but also for communication. In sign languages, for example, different hand gestures represent the letters of the alphabet. Sign languages are full-fledged languages that allow anything to be conveyed in the same way that any other language can. With the help of the hands, face and even the entire body, words and meanings are expressed as complex signs. To spell words or names for which no specific signs are available, sign languages also contain a finger spelling alphabet. For each letter of the alphabet, there exists a specific gesture that can be formed with one hand (see Fig. 5).

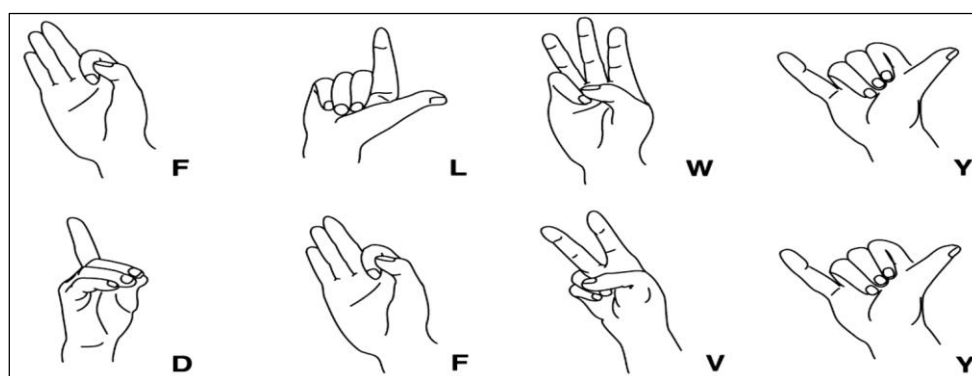


Figure 5. Participants had to execute one of four hand gestures taken from the American sign language alphabet. (For the fMRI study, the gestures 'L', 'F', 'W' and 'Y' and for the ECoG study 'D', 'F', 'V' and 'Y' were used)

The muscles of body, hands and fingers are controlled by a network of cortical and subcortical structures involving, among others, the cerebellum, the basal ganglia and the primary motor cortex. The topographic representation of body parts in primary motor cortex makes it easy to differentiate between the

movements of the different body parts (legs and arms) based on neuronal activity, and this topographic representation is also present for individual fingers. The hands and fingers are known to be extensively represented on the sensorimotor cortex at a specific anatomical landmark, the so-called hand knob. Moreover, it has been shown that the movement of individual fingers and the coordinated movements of all fingers can be discriminated based on the neuronal activity of the sensorimotor cortex. Consequently it should also be possible to decode communicative hand gestures.

It was studied the decodability of gestures using functional magnetic resonance imaging (fMRI). The fMRI provides valuable information that is difficult to acquire by other means. Twelve young healthy right-handed volunteers participated in the study, in which they had to execute four hand gestures taken from the American Sign Language alphabet (corresponding to the letters 'F', 'L', 'W' and 'Y'; see Fig. 5) inside the scanner. The participants were naive to the meaning of the signs prior to the experiment. In a familiarization session, they practiced the gestures and learned the corresponding letters. The execution of the gestures inside the scanner was recorded by an MRI compatible data-glove. This data-glove provides information about the flexion of each finger.

From the fMRI experiment [18], it was learned that the four hand gestures could be classified with a comparably high accuracy using only a small patch of cortex (on the gyrus). These results indicate that it is possible to distinguish different gestures, based on their single trial activation pattern, using a confined area of cortical tissue around the hand-knob region. Consistent execution of the gestures is essential for effectively discriminating the gestures. The most informative voxels were confined to a small patch of cortex surrounding the hand-knob area (Fig. 6).

The axial slices show nicely that the informative voxels cluster around the hand knob being partly located within the sulcus as well as on the gyrus.

Example 3. Emotional learning occurs mainly in the amygdala. The system operation consists of two levels: the amygdala learns to predict and react to a given reinforcement signal. This subsystem cannot unlearn a connection. The incompatibility between predictions and the actual reinforcement signals causes inappropriate responses from the amygdala. As depicted in Fig. 7, the system on Fig. 3b consists of four main parts [16].

Sensory input signals first enter the thalamus. Since the thalamus must provide a fast response to stimuli, in this model the maximum over all stimuli  $S$  is sent directly to the amygdala as another input. The amygdala receives inputs from the thalamus and sensory cortex, while the orbitofrontal cortex (OFC) part receives inputs from the sensory cortex and the amygdala. The system also receives a reinforcing signal ( $REW$  – emotional signal).

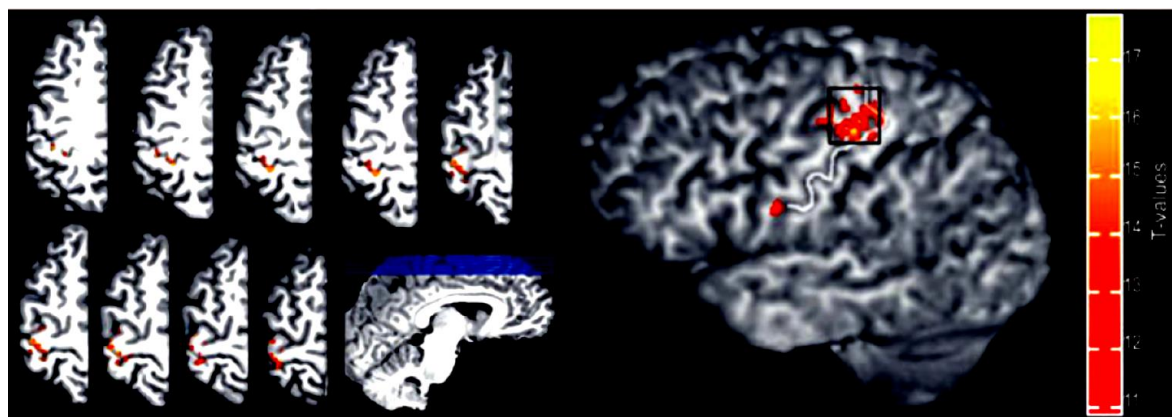


Figure 6. fMRI results: (Left) Location of the most informative voxels shown on the axial slices for one participant. The majority of informative voxels are located at the hand knob area. The informative voxels follow the characteristic Epsilon shape of the hand knob. (Right) Most informative voxels as projection to the cortex. The white line indicates the central sulcus, and the black square indicates the possible location of a high density [18]

For each  $A$  node in the amygdala, there is a plastic connection weight  $V_i$ . Any input is multiplied by this weight to provide the output of the node. The  $O$  nodes show similar behavior, with a connection weight  $W_i$  applied to the input signal to create an output. There is one output node in common for all outputs of the

model, called  $E$  (see Fig. 7a). The  $E$  node sums the outputs from  $A$  except for the  $A_{ih}$  and then subtracts the inhibitory outputs from the  $O$  nodes. The result is the output from the model.

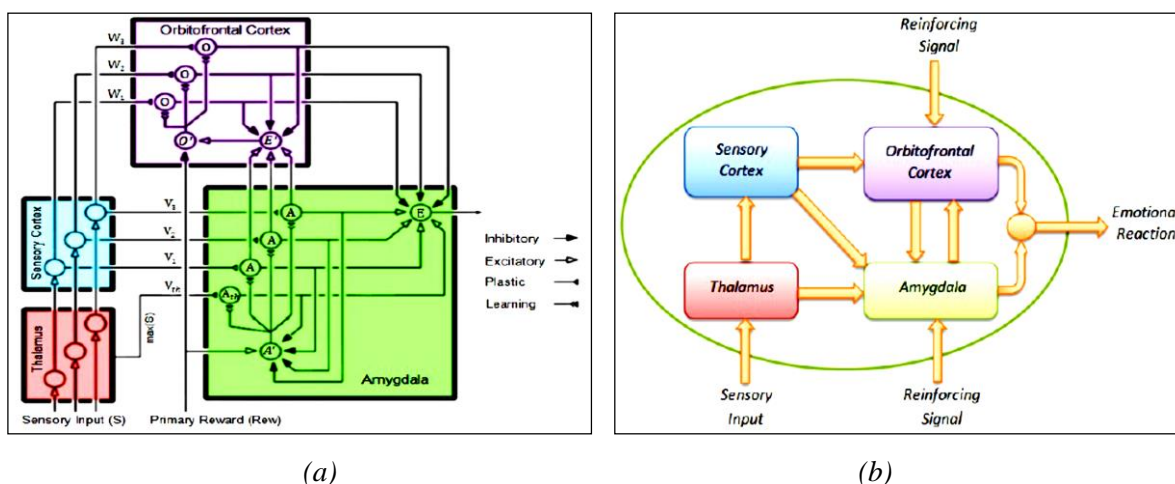


Figure 7. A Graphical depiction of the brain emotional learning process (a) and the process of generating emotional reactions in the limbic part of human brain (b)

The OFC learns to prevent the system output if such mismatches occur. The learning in the amygdala and the OFC is performed by updating the plastic connection weights, based on the received reinforcing and stimulus signals.

Let us consider briefly Brain Emotional Learning Based Intelligent Controller (BELBIC) structure [16].

In a biological system, emotional reactions are utilized for fast decision-making in complex environments or emergency situations. It is thought that the amygdala and the orbitofrontal cortex are the most important parts of the brain involved in emotional reactions and learning. The amygdala is a small structure in the medial temporal lobe of the brain that is thought to be responsible for the emotional evaluation of stimuli. This evaluation is in turn used as a basis for emotional states and reactions and is used for attention signals and laying down long-term memories. The amygdala and the orbitofrontal cortex compute their outputs based on the emotional signal (the reinforcing signal) received from the environment. The final output (the emotional reaction) is calculated by subtracting the amygdala's output from the orbitofrontal cortex's (OFC) output (see Fig. 7b).

It should be observed that it essentially converts two sets of inputs (sensory inputs and emotional cues or reinforcing signals) into the decision signal (the emotional reaction) as its output. Closed loop configurations using this block (BELBIC) in the feed-forward-loop of the total system in an appropriate manner have been implemented so that the input signals have the proper interpretations. The block implicitly implemented the critic, the learning algorithm and the action selection mechanism used in the functional implementations of emotionally-based (or, generally, reinforcement learning-based) controllers, all at the same time.

The policies for PID-based controller and the BELBIC controller are the same due to the equal number of states which are needed for the feedback. The structure of the control circuit that we implemented in this study using the direct-adaptive control strategy is illustrated in Fig. 8.

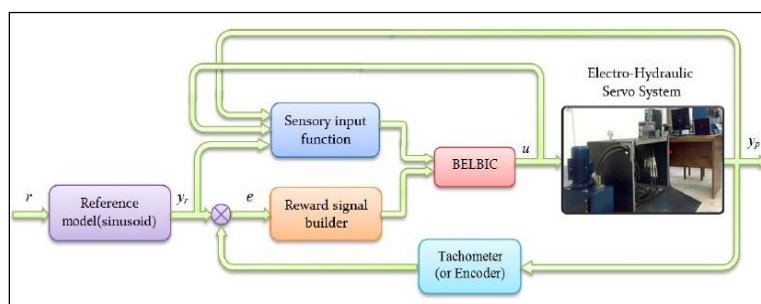


Figure 8. System configuration using brain emotional controller



The PID controller contains a constant steady-state position error, yet in the BELBIC the steady-state position error eventually decreases. Unlike the PID controller, learning the dynamics through real-time implementation causes the BELBIC to track the reference signal inaccurately at the beginning of the experiment (shown in [16]). Despite the fact that the initial weights are all set to zero, the BELBIC rapidly learns the dynamics of the plant without any off-line training. During transient states, a slight overshoot is observed in the control signal of the BELBIC since the servo-valve draws more current; however, in the PID-based controller no such change is realized. As the BELBIC passes on to a steady state, the control signal becomes uniform and smooth, which is an important advantage in practical use, especially in high power systems such as EHS systems. The energy consumption of the BELBIC is about the same as the PID controller, whilst the BELBIC has less tracking error. The BELBIC tracks the reference signal with very low error in comparison with the PID controller. The BELBIC displays good robustness to a change in the dynamics of the system, an acceptable overshoot and a good tracking ability (compared to the PID). A main advantage in the performance of the controlled EHS system is in the high degree of the adaptability of the control system and the robustness of the performance with respect to the initial error in relation to modelling and identification (even with a total lack of knowledge about the system model).

## 2. Quantum mechanics approach to biological neural information processing and brain activities of consciousness

Quantum mechanics is successful because of the close agreement between its theoretical calculations and experimental measurements. To take profit from such achievements, neurosciences has to incorporate the formalism necessary to understand the quantum events at the level of the neuron, which in turn is a necessity to the comprehension of the huge computational capacity of the brain. IT computing is currently built in vacuum and very cooled ions.  $\text{Ca}^{2+}$  is trapped in the water medium in the dendritic spine (organelles containing mitochondria situated adjacent to gap junctions between neighboring dendrites).

The main purpose is to invite both the quantum mechanics and neuroscience communities to joint efforts in order to open one of the last frontiers of the human investigation of this amazing machine: the brain. Modern neurosciences is disclosing the neuron as a very complex biochemical machine, in charge of the huge computations demanded by a brain that steadily evolves to take more and more control over the environment where it lives in. The simple McCulloch and Pits neuron, despite its important contribution to theoretical neurosciences in the early days, is no longer an adequate formalism to help the neuroscientist to understand the complexities of the primate brain. Any process at the cellular level nowadays understood as a dynamical set of biochemical transactions.

The brain is the most sophisticated processing machine developed by nature so far, and quantum information processing has been considered to model its function. Dendritic spines (DS) are specialized synaptic structures (see Fig. 9 [19]) allowing large, extremely rapid, long lasting and localized  $[\text{Ca}^{2+}]$  build up at the spine.

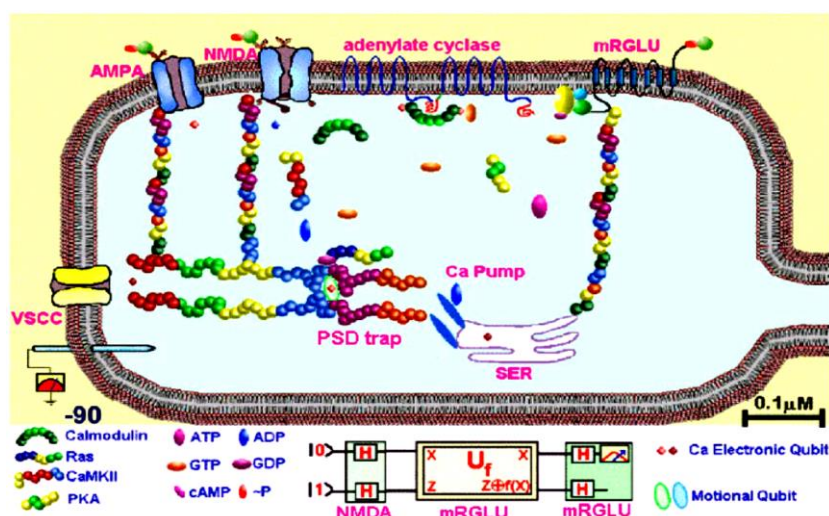


Figure 9. Sophisticated processing machine [18]

Remark 1. On Fig. 4 Step 1: Glu binding to the AMPA receptor and allows  $\text{Ca}^{2+}$  to move into the dendritic spines through AMPA and VSCC channels.  $\text{Ca}^{2+}$  entering this latter channel trapped in a narrow molecular cavity formed by PSD proteins. Step 2: Glu binding to the NMDA receptor allows  $\text{Ca}^{2+}$  to enter the spine and to bind to Calmodulin in order to activate CaMKII ((calcium/calmodulin-dependent kinase II) a protein molecule that adds phosphoryl groups to other molecules as a mechanism of activation), which in turn activates RAS that under GAP action liberates energy to performed a Hadamard gate. Steps 3 and 4: Glu binding to mRGLU activates a G-protein to stimulate Adenylate Cyclase to produce cAMP, which is used to activate PKA. PKA controls RAS to first implement  $U_f$  and then to perform another Hadamard gate. Step 4: Finally, the trapped  $\text{Ca}^{2+}$  is moved into the smooth endoplasmic reticulum (SER) by cAMP activated  $\text{Ca}^{2+}$  pumps. For details, see [www.eina.com.br/sensor](http://www.eina.com.br/sensor).

They are very plastic structures involved in both rapid (imprinting) and slow learning.

Basic to the understanding of DS as a quantum IT device is the physiology of the glutamate (Glu) and its receptors (Fig. 9): (a) AMPA ( $\alpha$ -amino-3-hydroxy-5-methyl-4-isoxazolepropionate) receptor: the Glu-binding to AMPA allows the entry of  $\text{Ca}^{2+}$  and promotes a depolarization of the membrane potential (EM), what facilitates  $\text{Ca}^{2+}$  entry through the voltage sensitive Ca channels (VSCCs in Fig. 8); (b) NMDA (*N*-methyl-D-aspartate) receptor: functions as a coincidence detector (CD), since the AMPA EM depolarization remove the  $\text{Mg}^{2+}$  attached to it, and a posterior Glu-binding within a temporal window (100 ms), allows new  $\text{Ca}^{2+}$  to move in and to bind to calmodulin, that controls the CaMKII kynase to deliver energy to other biochemical processes; (c) mR-Glu receptors: Glu-binding to mRGLu activates many types of G-proteins controlling other cellular processes. G-protein is a CD too (D. 200–600 ms). A set of proteins anchors Glu-receptors in the membrane by (Fig. 9).  $\text{Ca}^{2+}$  concentration inside the cell is controlled by pumping it outside the cell or to organelles (e.g., SRE in Fig. 9).

Glutamate and aspartate are known to be major excitatory transmitters in the cerebral cortex. Glutamate is also released by the sensory terminals in thalamus and it is assumed to be the transmitter in charge to convey sensory information to the thalamic relay neuron (TRN).

Remark 2. Glutamate binds to three different classes of membrane receptors:

1. Metabotropic receptors: glutamate binding to these receptors promotes the activation of G-proteins in charge of controlling different types of STPs;
2.  $\alpha$ -amino-3-hydroxy-5-methyl-4-isoxazolepropionate (kainate receptors): glutamate binding to these receptors opens ionic channels and depolarize the membrane (Fig. 10);
3. NMDA receptors: the effect of glutamate binding on this receptor depends on the electrical state of the membrane. In hyperpolarized states,  $\text{Mg}^{2+}$  ions bind to the inner core of the channel controlled by the receptor and block any other ion movement through the channel. Depolarization reduces the NMDA channel affinity for the  $\text{Mg}^{2+}$ , such that these ions may leave the channel. In this condition, glutamate binding opens the NMDA channel to  $\text{Ca}^{2+}$  ion entrance (Fig. 10).

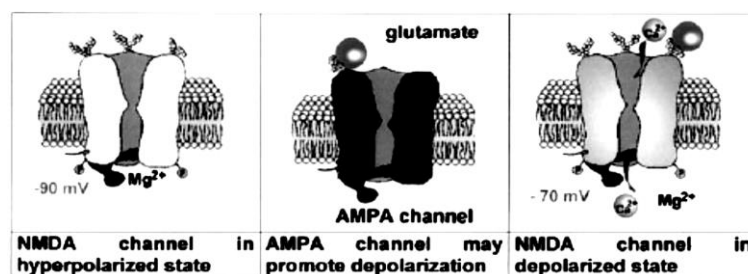


Figure 10. The coincidence detector system [20]

Basic to the understanding of DS as a quantum IT device is the physiology of the glutamate (Glu) and its receptors (Fig. 9): (a) AMPA receptor: the Glu-binding to AMPA allows the entry of  $\text{Ca}^{2+}$  and promotes a depolarization of the membrane potential (EM), what facilitates  $\text{Ca}^{2+}$  entry through the voltage sensitive Ca channels (VSCCs in Fig. 9); (b) NMDA receptor: functions as a coincidence detector (CD), since the AMPA EM depolarization remove the  $\text{Mg}^{2+}$  attached to it, and a posterior Glu-binding within a temporal window (100 ms), allows new  $\text{Ca}^{2+}$  to move in and to bind to calmodulin, that controls the CaMKII kynase to deliver energy to other biochemical processes; (c) mR-Glu receptors: Glu-binding to mRGLu activates many types of

G-proteins controlling other cellular processes. G-protein is a CD too ( $\Delta = 200\text{--}600$  ms). A set of proteins anchors Glu-receptors in the membrane by (Fig. 9).  $\text{Ca}^{2+}$  concentration inside the cell is controlled by pumping it outside the cell or to organelles (e.g., SRE in Fig. 9).

Let us consider the interrelations between quantum computing (QC) and sophisticated processing machine on Fig. 9 developed by nature.

Example 3: Deutsch-Jozsa's *algorithm* (DJA) was the first explicit example of a computational task performed exponentially faster using quantum effects than by classical means [14]. Given a one-bit function,  $f$  one have: (a) two constant functions  $f(0)=0$  and  $f(1)=0$ , or  $f(0)=1$  and  $f(1)=1$ ; or (b) two “balanced”  $f(0)=0$  and  $f(1)=1$ , or  $f(0)=1$  and  $f(1)=0$ .

A one qubit QC is able to decide if  $f$  is constant or balance in just one step. Starting with the standard state  $|0\rangle|0\rangle$  at the input ( $I$ ) and output ( $O$ ) registers, a NOT operation is applied to  $I$  and the Hadamard transformation ( $H$  in Fig. 4) is applied to both registers. Thus

$$|0\rangle|0\rangle \xrightarrow{\text{NOT}} |0\rangle|1\rangle \xrightarrow{H} \left( \frac{|0\rangle+|1\rangle}{\sqrt{2}} \right) \left( \frac{|0\rangle-|1\rangle}{\sqrt{2}} \right).$$

Next, the unitary transformation  $U_f$  is applied to both registers:

$$U_f : \left( \frac{|0\rangle+|1\rangle}{\sqrt{2}} \right) \left( \frac{|0\rangle-|1\rangle}{\sqrt{2}} \right) \rightarrow \left( \frac{1}{\sqrt{2}} \sum_{x \in B} (-1)^{f(x)} |x\rangle \right) \left( \frac{|0\rangle-|1\rangle}{\sqrt{2}} \right).$$

In this condition,  $O$  remains in the state  $\left( \frac{|0\rangle-|1\rangle}{\sqrt{2}} \right)$  and  $I$  is left in the state.

Therefore if  $f$  is constant  $I$  is  $\pm \left( \frac{|0\rangle-|1\rangle}{\sqrt{2}} \right)$  and if  $f$  is «balanced» it is  $\pm \left( \frac{|0\rangle+|1\rangle}{\sqrt{2}} \right)$ .

If  $H$  is applied again to  $I$ , it becomes  $\pm(|0\rangle)$  if  $f$  is constant and  $\pm(|1\rangle)$  if  $f$  is “balanced”. These states are reliably distinguished by a measurement in the standard basis, thus distinguishing balanced from constant functions after just one query. DJA was implemented in a  $\text{Ca}^{2+}$ ITC [19].

Therefore, any proposal of biological QC should be able to demonstrate the possibility of a biological structure to fulfill such requirements.

Two of the most surprising properties of quantum systems are state superposition and entanglement. Superposition is the coexistence of different state values of the same particle at the same time. Superposed states are reduced to a single one by the act of measurement or by other kinds of interaction with the macro-environment, which are called decoherence. Entanglement is a strong state correlation between spatially separated particles.

Coincidence detector (CD) was proposed to create entangled quantum states in the brain. The rationality is the following (Fig. 9) [19]:

(1) A first Glu released binds to the AMPA channel promoting EM reduction,  $\text{Mg}^{2+}$  release from the NMDA channel, VSCC activation and  $\text{Ca}^{2+}$  entry. These  $\text{Ca}^{2+}$ s are physically trapped by proteins in a molecular cavity of typical size of  $0.7 \text{ \AA}$  (bigger than  $\text{Ca}^{2+}$  radii) in the spine.

(2) A second release of Glu within  $\Delta = 100$  ms, allows new  $\text{Ca}^{2+}$  to bind to calmodulin to provide energy to create state superposition and entanglement of the trapped  $\text{Ca}^{2+}$  ions. The electronic qubits are  $|0\rangle = s^1$  and  $|1\rangle = 3p^0$  and the required energy is in the band of 50 nm (UV). The motion qubits are  $|0\rangle =$  ground state and  $|1\rangle =$  first excited state, with ground state energy of 3.2 eV.

(3) A third Glu release over mR-Glu within  $\Delta > 100$  ms, activates G-proteins to deliver energy to manipulate the entangled  $\text{Ca}^{2+}$ .

DS process the DJA as follows (Fig. 10) [19]. The AMPA channel is associated to  $O$  whereas the VSSC is assigned to  $I$ . EM depolarization promoted by  $\text{Ca}^{2+}$  entry through the AMPA channel remove the  $\text{Mg}^{2+}$  from the NMDA channel and opens VSCCs. Next, NMDA channel activated, and CaMKII controlled RAS is used to perform the Hadamard transformation upon the  $\text{Ca}^{2+}$  trapped in the post-synaptic density (PSD).

Next, mR-Glu receptor is activated, and a G-protein is used to control the implementation of  $U_f$ . The same G-protein controls the energy to perform another Hadamard transformation. Finally the  $\text{Ca}^{2+}$  transporting into SER is used to read the result. A point worth to remark is that DS is amenable to many different and sophisticated experimental manipulations.

Now, let's suppose another function  $f: B^n \rightarrow B$  that is either constant if the  $2^n$  values are either 1 or 0, or balanced if exactly half (i.e.  $2^{n-1}$ ) of the values are 0 and half are 1. DJA is extended to treat such kind of function, if one starts with a row of  $nI$  qubits and one  $O$  qubit and to applies the same step procedures above.

At the end, the  $n$  is are 1 in state  $|\xi_f\rangle = \left( \frac{1}{\sqrt{2^n}} \sum_{x \in 2^n} (-1)^{f(x)} |x\rangle \right)$ .

If  $f$  is constant then  $\xi_f$  will be just an equal superposition for all the  $|x\rangle$ 's with an overall plus or minus sign, whereas if  $f$  is a balanced function then  $\xi_f$  will be an equally weighted superposition with exactly half of the  $|x\rangle$ 's having the minus signs. Recalling that  $H$  has its own inverse ( $HH = 1$ ) and that  $H$  applied to each qubit  $|0\rangle$  of  $|\xi_f\rangle$  results in an equal superposition of all  $|x\rangle$ 's. Therefore, if  $f$  is constant then the resulting state is  $x = \pm|0\rangle|0\rangle\ldots|0\rangle$ , and if it is balanced then  $|x\rangle$ 's is  $x \neq |0\rangle|0\rangle\ldots|0\rangle$ . The reading of each of the  $n$  qubits completes the measurement. DJA requires  $O(n)$  steps to distinguish balanced from constant functions, whereas classical algorithm demand  $O(2^n)$  steps for the same task. However, a probabilistic algorithm is able to solve the same task in  $k$  steps with a probability of  $(1 - \zeta)$  for correct answer and  $\zeta$  less  $1/2^k$ .

The presence of typically quantum effects, namely superposition and interference, in what happens when human concepts are combined, and provide a quantum model in complex Hilbert space that represents faithfully experimental data measuring the situation of combining concepts.

Example 4. *Quantum interference in cognition*. Let us now explicitly construct a quantum mechanical model in complex Hilbert space for the pair of concepts *Fruit* and *Vegetable* and their disjunction "*Fruit or Vegetable*", and show that quantum interference models the experimental data gathered [21]. In Fig. 11 the data for "*Fruits or Vegetables*" are graphically represented.

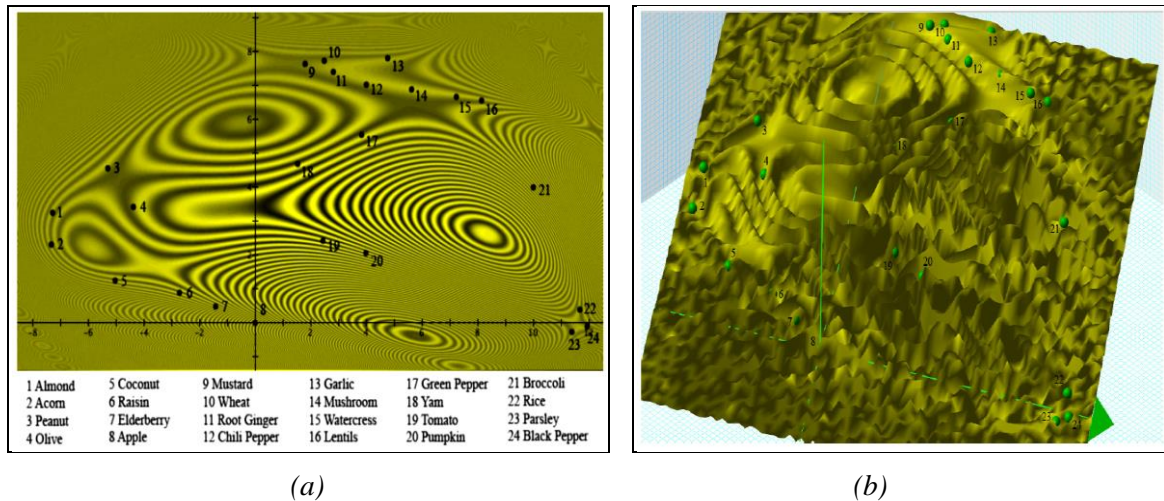


Figure 11. The probabilities  $\rho(A \text{ or } B)_k$  of a person choosing the exemplar  $k$  as an example of 'Fruits or

Vegetables' are fitted into the two-dimensional quantum wave function  $\frac{1}{\sqrt{2}}(\psi_A(x, y) + \psi_B(x, y))$ , which is the normalized superposition of the wave functions (a); and A three-dimensional representation of the interference landscape of the concept 'Fruits or Vegetables' as shown in Fig. 11a (b) [21]



This is just a normalized sum of the Gaussians, since it is the probability distribution corresponding to  $\frac{1}{\sqrt{2}}(\psi_A(x, y) + \psi_B(x, y))$ , which is the normalized superposition of the wave functions. The numbers are placed at the locations of the different exemplars with respect to the probability distribution

$$\frac{1}{2}|\psi_A(x, y) + \psi_B(x, y)|^2 = \frac{1}{2}(|\psi_A(x, y)|^2 + |\psi_B(x, y)|^2) + |\psi_A(x, y)\psi_B(x, y)|\cos\phi(x, y)$$

where  $\phi(x, y)$  is the quantum phase difference at  $(x, y)$ . The values of  $\phi(x, y)$  are given for the locations of the different exemplars in [21].

The interference pattern shown in Fig. 11 is very similar to well-known interference patterns of light passing through an elastic material under stress. In considered case it is the interference pattern corresponding to “*Fruits or Vegetables*”. The interference pattern is clearly visible. The model shows how “interference of concepts” explains the effects of under extension and overextension when two concepts combine to the disjunction of these two concepts. This result supports hypothesis that human thought has a superposed two-layered structure, one layer consisting of classical logical thought and a superposed layer consisting of quantum conceptual thought. Possible connections with recent findings of a grid-structure for the brain are analyzed, and influences on the mind / brain relation, and consequences on applied disciplines, such as artificial intelligence and quantum computation [22].

### 3. Quantum self-organization models

In recent years, the concept of self-organization has been used to understand collective behavior of human being society, animals, ant's, bird's, bacteria's 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 spiraling chemical waves, which arise without complexity at the level of the individual units of which the system is composed.

#### 3.1. A general characteristic of self-organizing systems

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 analyzed 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<sup>1</sup>.

Models of self-organization are included 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 exchange and is explained by increased entropy on a micro-level); (ii) communication and information transport on micro-level

<sup>1</sup> I.A. Barchatova. Role of information-thermodynamic trade-off models of control qualitative in quantum control algorithm of self-organization design // System Analysis in Science and Education. – 2014. – № 3.

(“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; (ii) self-assembling; and (iii) self-organization.

According 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 developed below is based on quantum fuzzy inference (QFI) model [12]. QFI includes these concepts of self-organization and has 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* is realized *templating* operation, and based on macro- and micro-level interactions with information exchange of active agents. *Selection* of quantum correlation type organize *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 are 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 [12, 22].

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 [23]. For locally unstable control object (with weak and rough defined structure) the robustness of sub-optimal solutions of control laws are demonstrated [12].

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 are used two and three KBs designed with soft computing optimizer, correspondingly. It is 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 in on-line with new types of quantum correlations from responses of fuzzy PID-controllers (with fixed knowledge bases) on unpredicted control situation.

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

### 3.2. Background of quantum self-organization

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 [24 – 26].

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 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 [25]: 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 on line 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 [25].

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 [24 – 26], 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.

### 3.3. 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 are used the information from micro-level that support thermodynamic relations (second law of thermodynamics: increasing and decreasing of entropy on micro- and macro-levels, correspondingly) of dynamic evolution; (ii) Self-organization processes are used 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 natural self-organization processes are don't planning 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 are used current classical information for decision-making (but don't have toolkit for extraction and exchanging of hidden quantum information from dynamic behavior of control object).

In man-made 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*.

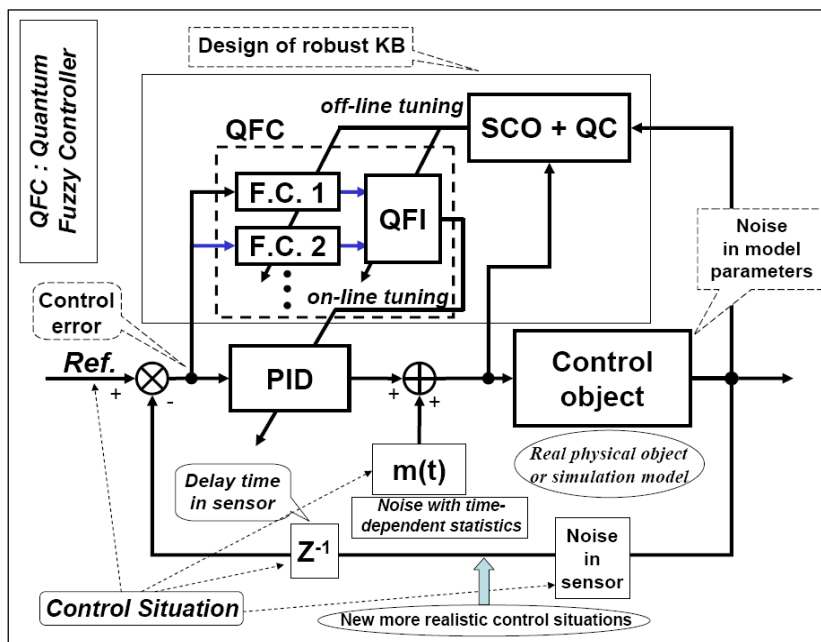
*Remark.* The developed quantum control algorithm includes three possibilities: (i) from the simplest living organism composition in response to external stimuli of bacterial and neuronal self-organization; and (ii) according to correlation information stored in the DNA; (iii) from quantum hidden correlations 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 [12]. Below we will describe the Level 1 (see, Fig. 13) based on QFI model as the background of robust KB design information technology.

QFI model is described in details in [12, 23] and used here as toolkit.

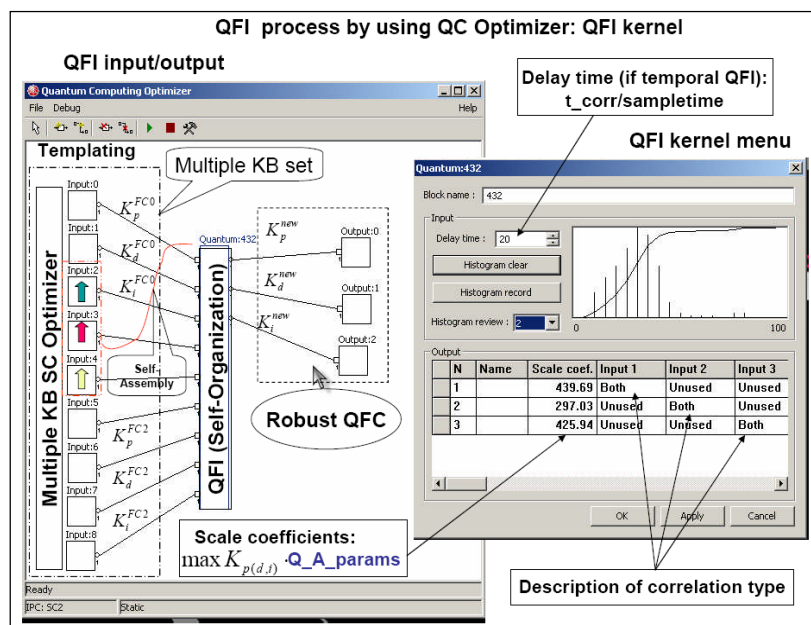
18

The structure of robust intelligent control system in unpredicted control situations is shown on Fig. 13.



This structure is the particular case of general structure of IFICS (see Fig. 12).

Graphical interface of Quantum Fuzzy Inference (QFI) is shown in Fig. 14.



Detail description of graphical interface and quantum fuzzy inference are described in [12].

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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.

Thus results of simulation show that winner is quantum fuzzy controller (QFC) designed from two KB controller 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 important the new result for advanced control system that all other controllers (FC1, FC2) are failed but QFC is designed with increasing robustness. This approach was applied to other complex robotic systems. Concrete Benchmarks are described in details with the application of intelligent control system in Figs 8 and 9 as following.

## 5. Examples of solutions

### 5.1. 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 mechanism 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 [9, 27, 28].

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 accordingly to the model representation results of [28]. 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 15 and 16 are demonstrated the unicycle model and results of simulations.

In particular, Fig. 15 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. 16.



A white, helmeted humanoid robot with a single large wheel at its base is positioned on a wooden floor. The robot has a friendly, rounded face and a small antenna. It is surrounded by several children who are sitting or crouching on the floor, looking at it with interest. One child in the background is holding a camera up to take a picture. The setting appears to be a museum or an educational center with wooden walls and floors.

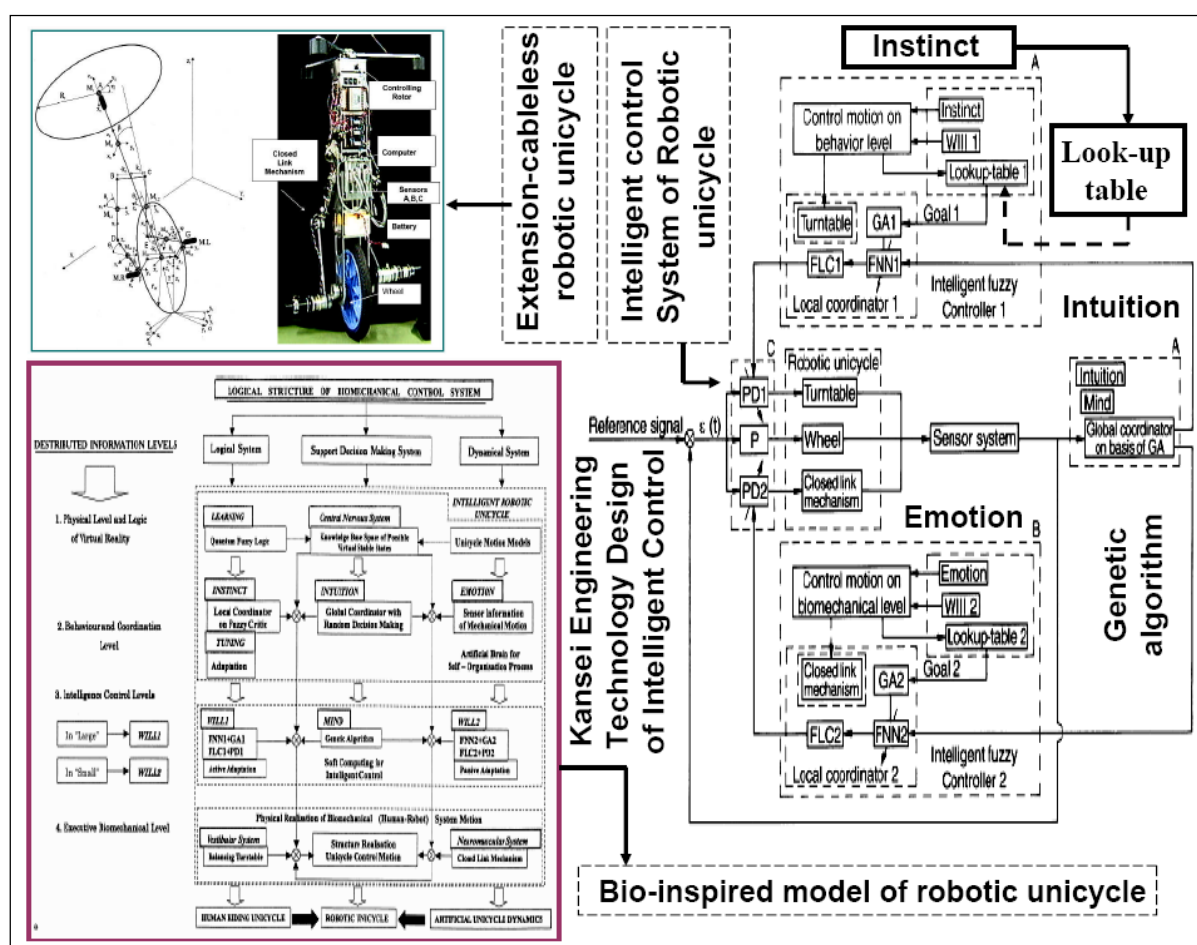
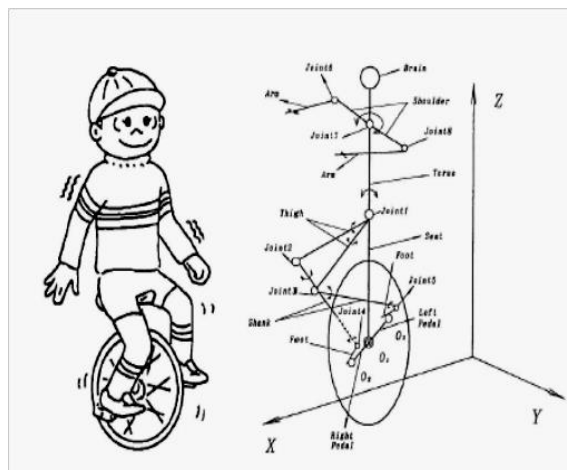
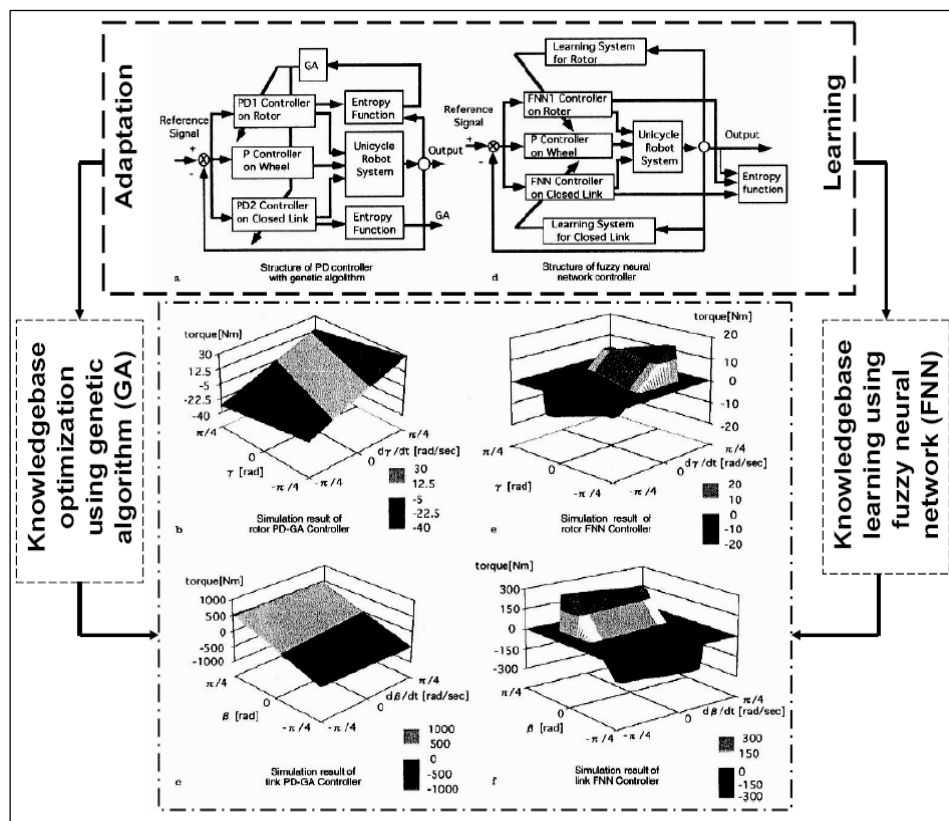


Figure 15. Robotic unicycle model

Thus, an instinct mechanism produces less entropy than an intuition mechanism. However, the necessary time for achieving an optimal control with the learning process on FNN (instinct) is larger than that with the global search on GA (intuition). The general approach for forming a lookup-table with GA and the fuzzy classifier system based on FNN is described in [26]. 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 GA and 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.



(a)

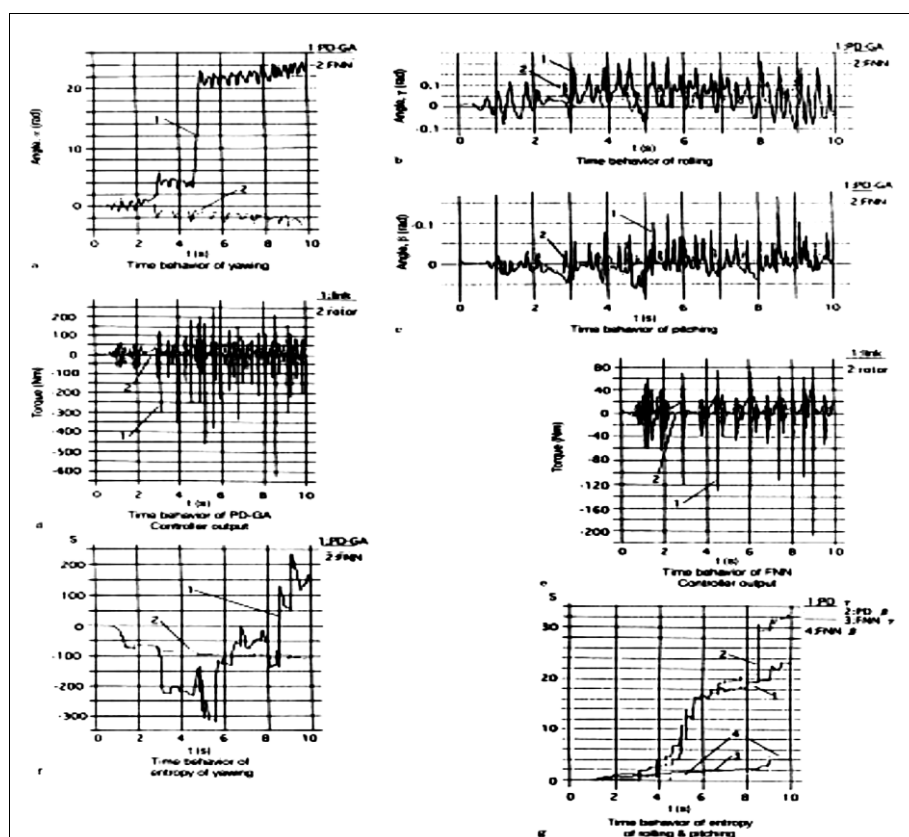


Figure 16. System simulation (a); and simulation results of mechanics and thermodynamic behavior (b) of robotic unicycle model

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 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 [28] 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.

Other examples are considered in [31 – 34] (<http://www.qcoptimizer.com/>).

Thus, we provide a *new benchmark* of Kansei engineering 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.

### 5.2. 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 on line 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. 17).

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 and these soft computing are described in [29]. The locomotion control system is composed of four functions, i.e. locomotion control, planning for works, learning and recognition.

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 [30]. 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. 18.

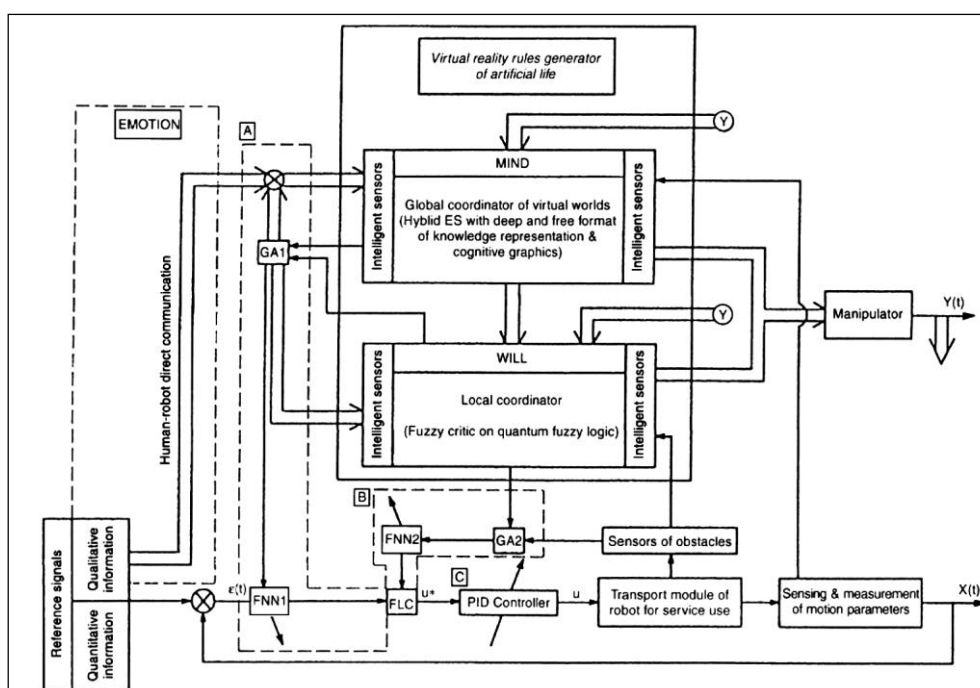


Figure 17. Structure of AI control system with distributed knowledge representation (on control signal levels). a - Intelligent control “in large” b - Intelligent control “in small” c - Control on executive level

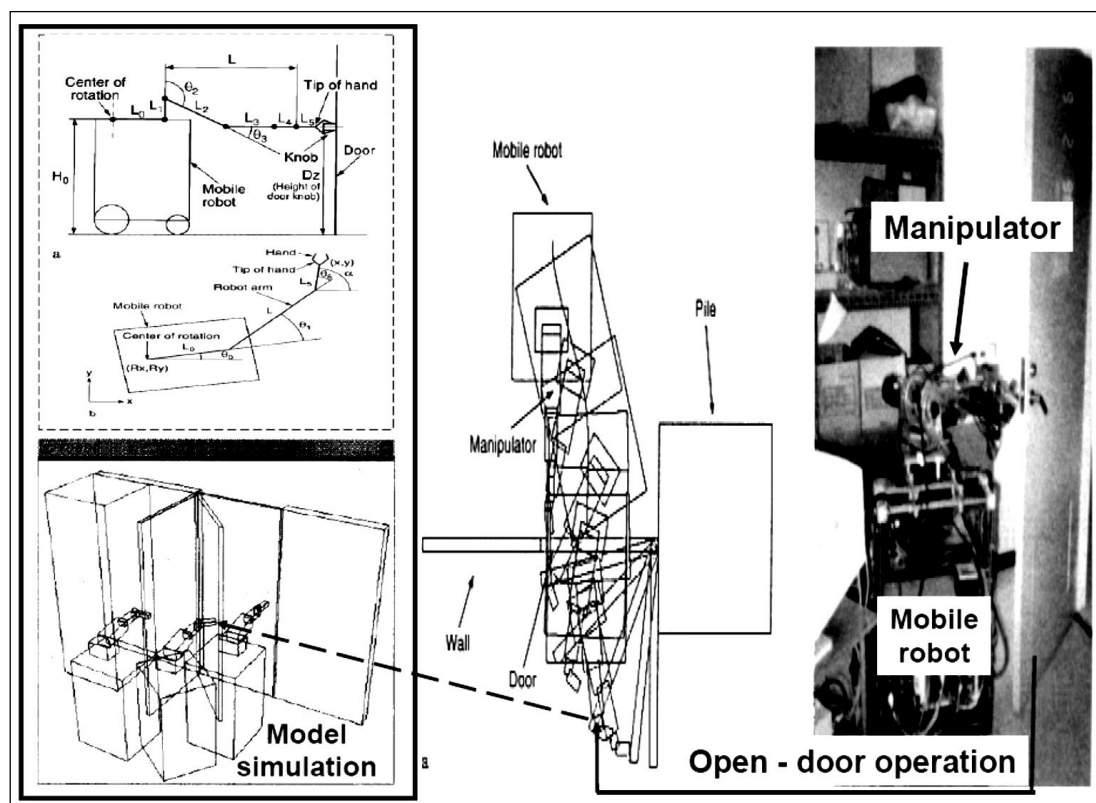


Figure 18. Mobile robot for service use

Example 5: *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. 19).

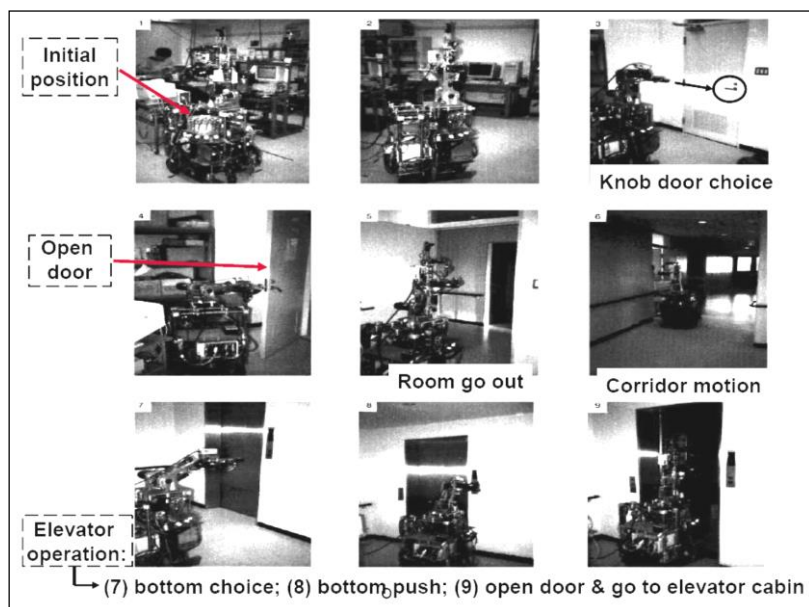


Figure 19. Navigation of mobile robot for service use

In process of robot's locomotion in a building on Fig. 19 from point to point mobile robot must avoid obstacles in Room, and achieve starting position for successful opening room door [30] (as technology operation from one point to another point) and go out 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 [29]. Technological operation's design of robot for service use is a new Benchmark [29] of human – machine interaction and of evolutionary intelligent computing in non-linear mechatronics and intelligent smart control. Other examples in [27 – 34] are described.

## Conclusions

1. New design effect in advanced control theory and design technology of intelligent control system based on Kansei Engineering is demonstrated.
2. 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.
3. 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.
4. Structure of SW-support as QFI tool is described.
5. 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.
6. Quantum fuzzy controller (QFC) based on QFI is demonstrated 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.

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