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ARTICLE

Robotic Smart Prosthesis Arm with BCI and Kansei / Kawaii / Affective Engineering Approach. Pt I: Quantum Soft Computing Supremacy

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ABSTRACT

A description of the design stage and results of the development of the conceptual structure of a robotic prosthesis arm is given. As a result, a prototype of man-made smart prosthesis on a 3D printer as well as a foundation for computational intelligence presented. The application of soft computing technology (the first step of IT) allows to extract knowledge directly from the physical signal of the electroencephalogram, as well as to form knowledge-based intelligent robust control of the lower performing level taking into account the assessment of the patient's emotional state. The possibilities of applying quantum soft computing technologies (the second step of IT) in the processes of robust filtering of electroencephalogram signals for the formation of mental commands of robotic prosthetic arm discussed. Quantum supremacy benchmark of intelligent control simulation demonstrated.

1. Introduction

The development of robotic human limbs prostheses and the production of human-like electromechanical devices - anthropomorphic robots are receiving more, but not sufficient, attention in both the scientific, technical and socio-economic plants [1-4]. It should also be noted that in the strategy for the development of artificial intelligence (AI) in the Russian Federation [5] in the *Healthcare* section, the application of AI in such an important socio-technical domain as intelligent prosthetics and smart cognitive control systems, as well as rehabilitation of disabled people, is not indicated at all.

Principles of the development and application of intelligent information technologies in the field of intelligent control using cognitive technologies ("brain-computer-device" interface - BCI) are considered. Neurointerface of this type (manmade interface) allow to restore and expand the capabilities of a person with physical (for example, disability with loss of limbs) or mental disorders in various activities (for example, autistic children or patients with impaired mental activity - dementia). Cognitive interfaces provide the ability to communicate, evaluate emotions, transfer and control devices with mental commands.

The process of developing a cognitive intelligent simulator toolkit discussed. The application of developed tool-

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kit provides developers with the ability to control robotic devices at the lower (executive) level (using the so-called "mental commands"), and at the upper level - the intelligent level (to develop cognitive intelligent control technologies with the possibility of application in applied tasks).

Let us consider briefly main principles, peculiarities and features of cognitive intelligent control applied in biomechanical products and presented the description of a hierarchical intelligent control system based on QSCOptKB™ (knowledge base optimizer on quantum soft computing).

2. Cognitive Intelligent Control: Design Principles and Features of Biomechanical Product

Sources of technological and breakthrough innovations in these areas are following: (1) new technologies for creating intelligent materials; (2) technologies for creating an intelligent software product integrated into devices and applied at all stages of interaction with devices; (3) new human-machine interfaces, the principles of which are based primarily on the method of reading the activity of the functioning of the brain and nerve endings of the body [2,5].

So, the *first* direction allows a person to restore (and in the future, to exceed) the functional state of limbs damaged as a result of any injuries due to the creation of more advanced alloys, material structures, nano coatings. The *second*, innovative direction is associated with the creation of sophisticated software that allows the biomechanical device to learn and adapt to individual physiological and psychological qualities and characteristics of the human operator. Through the application of deep machine learning and medical recommendation systems with a deep knowledge representation, it is possible to recognize complex human commands, read and recognize the emotional state of the operator [6 - 8]. At the same time, a certain computing basis in the form of embedded end-to-end technologies of cognitive computing and computational intelligence must correspond to software of this level. The development of the *third* direction based on the sources of new human-machine interfaces that can effectively complement and expand human information capabilities. Such interfaces include infrared - spectrometers, electroencephalographs, magnetoencephalographs, cognitive helmets and equipment for virtual and complementary (augmented) 3D - and 4D - reality, invasive and non-invasive sensors and beacons, for example, mounted on the wrist, or other parts of the human body [9 - 15].

2.1 Related Works

Many researches known in which patients routinely apply such interfaces to solve everyday problems and control various devices. Interfaces are actively used for rehabilitation and diagnostic procedures, helping to improve interaction with the human environment, including with robotic devices [10-14,16,17]. Technologies are actively involved quantum end-to-end technologies in EEG data processing and educational processes at state levels [18]. Research of this kind has been funded by states since the early 70's. There are a number of research collaborations on the creation and development of man - machine interfaces associated with all three areas [10-14,19,20] etc. In particular, research in this area can divided into the following groups:

(1) Recognition research - development of devices for the diagnosis, modeling, simplification and reduction of threats to the interaction of the brain with the system.

(2) Simulation of the brain mechanism - the use of neural network effects and the phenomena of the functioning of the brain in applied problems of information technology, for example, analysis and synthesis of information.

(3) Restorative medicine - restoration of behavioral cognitive functions lost as result of damage to the brain or body [8].

(4) Elaboration - development of brain-computer systems in the feedback loop to accelerate and improve the functional behavior of the system [1, 21].

The development of these researches made it possible to create new technologies for the neural interface to detect fundamental and interregional brain functions in online, as well as to develop complex mathematical algorithms to model brain activity and the resulting behavioral functions and reactions.

2.2 Architecture of the Limbic System

The Limbic System, as part of the mammalian creatures' brain, is mainly in charge of the emotional processes. (see Appendix 1). The Limbic System located in the cerebral cortex consists mainly of following components: Amygdala, Orbitofrontal Cortex, Thalamus, Sensory Cortex, Hypothalamus, Hippocampus and some other less important areas. We try to describe briefly these main components and their tasks.

Figure 1 illustrates the anatomy of the main components of Limbic System [22].

The first sign of affective conditioning of the system appears in Amygdala which is a small almond-shaped in sub-cortical area. This component placed in a way to communicate with all other Sensory Cortices and areas within the Limbic System.

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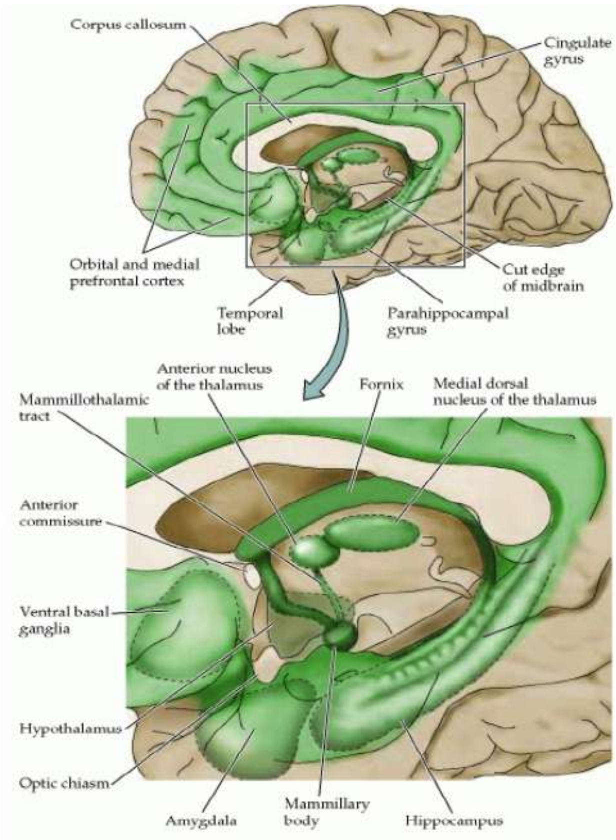

Figure 1. The major brain structures associated with the Limbic System [22]

The Amygdala connections to other components illustrated in Figure 2 [23].

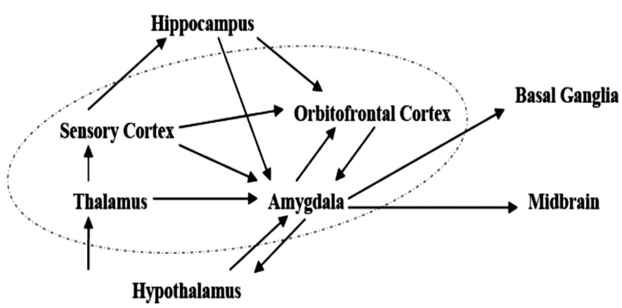

Figure 2. Connections of the Amygdala with other components of the Limbic System [23]

The studies show that a stimulus and its emotional consequences are associated in the Amygdala area. In this region, highly analyzed stimuli in the Sensory Cortices, as well as coarsely categorized stimuli in the Thalamus are associated with an emotional value. Furthermore, one of the most complex and twisting components of the Limbic System is Hippocampus which is located in the same area as the Amygdala. Its main role is the mapping of the environment based on environmental cue. The Hippocampus has other functions such as spatial navigation, laying down of the long-term memory and formation of the contextual representations there are other components, which have specific role in the Limbic System. To that extent components such as Basal Ganglia, Globus Pallidus, Substantia Nigra, Subthalamic Nucleus and Periamygdaloid Cortex could be mentioned. Since in this paper, biological description of the Limbic System is not under focus, it has been tried to avoid detailed and comprehensive explanation of each component. We deal with the key characteristics components in the System.

A computational model developed that mimics Amygdala, Orbitofrontal Cortex, Thalamus, Sensory Input Cortex and generally those parts of the brain thought responsible for processing emotions.

Figure 3 shows the computational model of emotional learning [24].

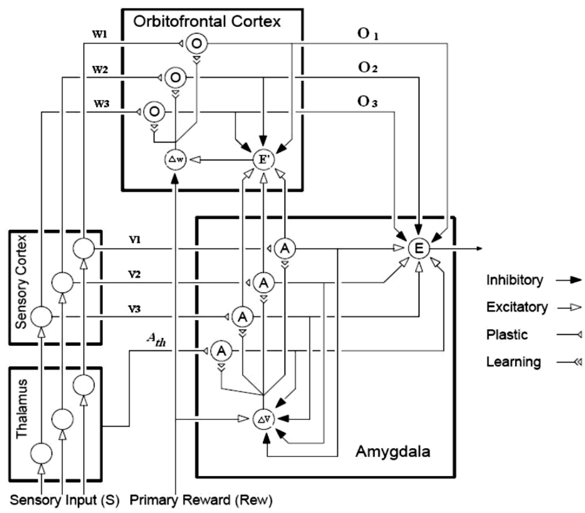

Figure 3. Graphical depiction of the Brain Emotional Learning (BEL) process [24]

The model divided into two parts: The Amygdala and the Orbitofrontal cortex. The Amygdala part receives inputs from the Thalamus and from cortical areas, while the Orbitofrontal obtains inputs from the cortical areas and the Amygdala. The system also receives a reinforcing signal (Primary Reward) which been left unspecified, as it is still uncertain from where it comes.

2.3 Brain Emotional Learning Based Intelligent Controller

Based on the cognitively motivated open loop model, BELBIC- Brain Emotional Learning Based Intelligent Controller- was introduced by Lucas et al [24, 25]. The intelligent controller has been utilized by several industrial applications and control purposes. The model of Figure 3 illustrated as control blocks in Figure 4 [25].

The BELBIC is essentially an action generation mech-

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anism based on sensory inputs and emotional cues (Reward signals) (see Appendix 1).

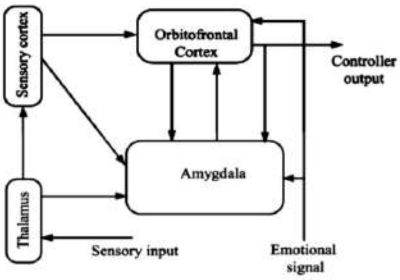

Figure 4. Basic block structure of emotional controller [25]

Figure 5 demonstrates a reasonable candidate for embedding the BELBIC model within a typical feedback control block diagram [25]. The implemented functions in emotional cue and sensory input blocks defined for each application [22 - 25].

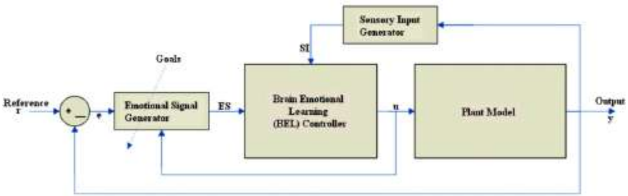

Figure 5. Control system configuration using BELBIC [25]

Example. A locally linear learning algorithm called Locally Linear Mode Tree (LoLiMoT) applied to build the neuro - fuzzy model. Then, the BELBIC based on PID control adopted for the micro-heat exchanger plant. The performance of presented controller compared with classic PID - controller. Figures 6a and 6b show the closed-loop system response using BELBIC and PID - controller respectively.

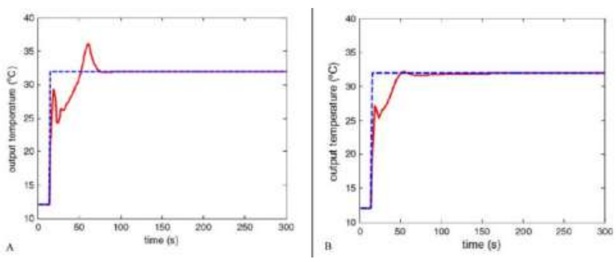

Figure 6. Closed - loop system response using PID with LoLiMoT identifier [26] (a).Closed-loop system response using BELBIC with LoLiMoT identifier [26] (b)

As shown the performance of the system using BELBIC is much better than that of PID controller.

Example. Figure 7a demonstrates afferent somatosensory signal that taken from the prosthetic device and is fed into the brain, from where the motor signal is sent back to the prosthetic limb. The nerve endings (located at the red circle). Figure 7b, still present at the site of the amputation, send signals (red arrows) or the cortical reorganization (red star in the brain) generates the phantom limp pain. Other sensations that can felt involve tingling, cramping, heat, and cold.

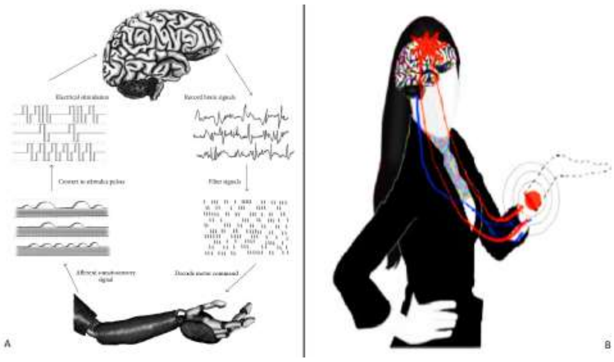

Figure 7. Working of neural prosthetics using a brain-machine interface (a). Phantom limb pain depiction (b)

Depending on the type of amputation, (see Table 1) the most suitable type of prostheses selected (see Figure 8a). The choice of prosthesis design determined by the position of phantom pains (see Figure 7b). On Figure 8b presented an artificial limb which replaces an arm missing above the elbow. The complexity of the artificial limb depends on the level of amputation.

Table 1. Presents Classification of Prosthetic as per amputation

N	Type of Amputation	Type of Prostheses
1	Shoulder disarticulation	From Shoulder
2	Elbow disarticulation	Below Elbow
		Above Elbow
3	Wrist disarticulation	Below Elbow
4	Trans carpal disarticulation	Below Elbow
5	Finger amputations	Below Elbow

Automated Prosthetic arms considered as biomedical devices and developing the same is interdisciplinary activity, i.e. combination of mechanisms and electronics. The selection of prosthetic arm depends upon type of the disarticulation the patient has undergone and the patients need.

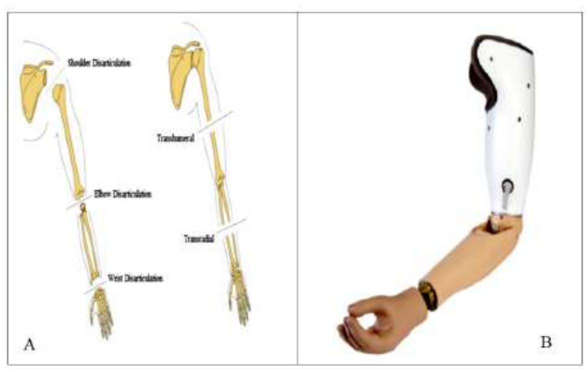

Figure 8. Amputation level (a). Transhumeral Prosthesis (b)

Figure 9 shows some of the ways to determine fundamental and interregional brain functions online: behavioral functions and reaction control of robotic limb prosthetics using different BCI.

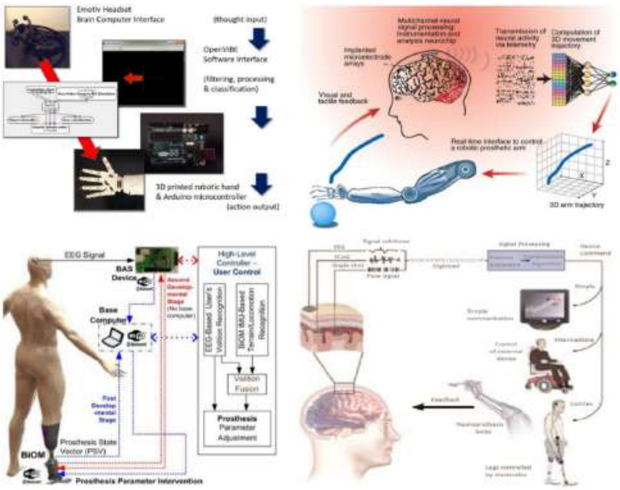

Figure 9. Detect fundamental and interregional brain functions in on line: behavioral functions and response control of robotic prosthetics limb with BCI

Figure 10 shows the generalized structure of an intelligent cognitive control system with feedback based on deep machine learning using artificial neural networks with an optimal structure, taking into account existing approaches to the cognitive control of a robotic prosthetic arm [27 - 29].

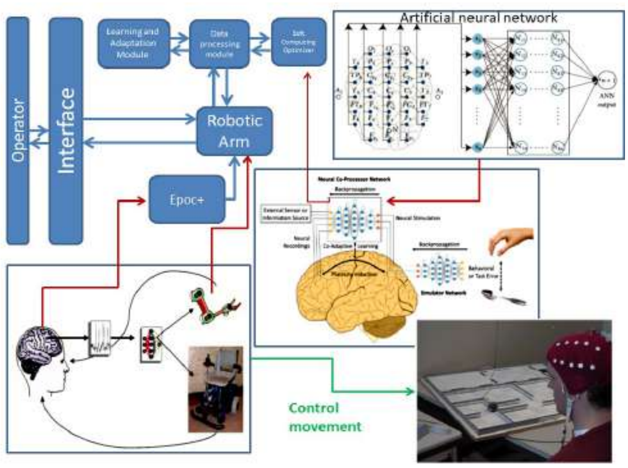

Figure 10. The structure of cognitive intelligent control system

In the considered part of the work cycle, the existing hardware and software research basis and information technology of sophisticated class of cognitive intelligent control system (see Figure 11) for supporting the design and operation of a new class of devices are presented.

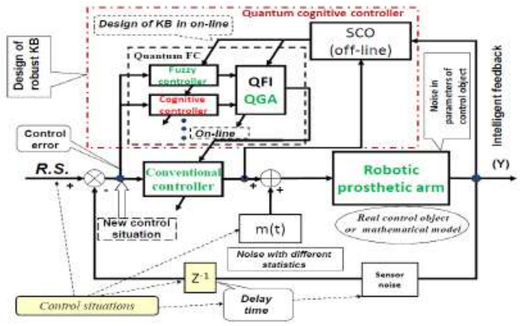

Figure 11. Structure of Quantum cognitive intelligent control system

Remark. According [17] the application of quantum neural network in filtering processing of EEG signals increase the accuracy of the filtering processing. The architecture of recurrent quantum neural network (RQNN) model is based on the principles of quantum mechanics with the Schrodinger wave equation playing a major part. This approach enables the online estimation of a time-varying probability density function that allows estimating and removing the noise from the raw EEG signal and demonstrate quantum supremacy in signal data processing. Applications of sophisticated intelligence toolkit (QSCOptKB™) include universal approximating functions of RQNN with optimal structure for quantum deep machine learning and achieved quantum soft computing supremacy [21] (see below Figures 23 and 24).

Structure of cognitive intelligent control system on Figure 11 includes two controllers: fuzzy and cognitive controllers. Design of fuzzy controller and of cognitive controller KBs is achieved with SCOptKB™ toolkit [30, 31]. In this case the responses of fuzzy and cognitive controllers in general case with imperfect KB are inputs for box “quantum fuzzy inference (QFI)” and the output of QFI is robust KB of self-organized controller for forming in on line time dependent control laws of coefficient gain schedule for conventional controller of robotic prosthetic arm.

3. Cognitive Intelligent Control of the Prosthetic Arm: Quantum Soft Computing Approach

Let us consider the redistribution problem of the level of responsibility between the cognitive and fuzzy controller. The basis of prostheses and robotic manipulators is spatial mechanisms with many degrees of freedom. Accordingly, when designing a cognitive intelligent controller for a prosthesis, the intelligent control system of the robotic arm can take as the basis. In this example, three fuzzy controllers are implemented in the structure of the intelligent control system of the robot manipulator with 3

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Degrees of Freedom (DoF), each of which controls one of the three links independently (see Figure 12).

Among unforeseen situations, the management distinguish external and internal. To external unforeseen situation it is customary to include disturbing influences - such as a forced change in the position of the control object at the beginning or in the process of working, changing the reference signals, etc. Internal control situations include changes to the parameters of the components of the control system (limits, noise, and signal delays). In details, intelligent control system on soft computing described in [30 - 32].

To prevent the negative effects of unforeseen situations in control, a quantum fuzzy inference (QFI) unit integrated in the control system of the robot manipulator, with the application of which KB self-organization in FC is realized. In this case, it is possible not only to combine information about the standard situation for three links, but also to extract additional information (by methods of quantum computing and quantum information theory) from the response of the designed KB for the implementation of robust control in regular and unforeseen control situations (which are not included in existing designed KB).

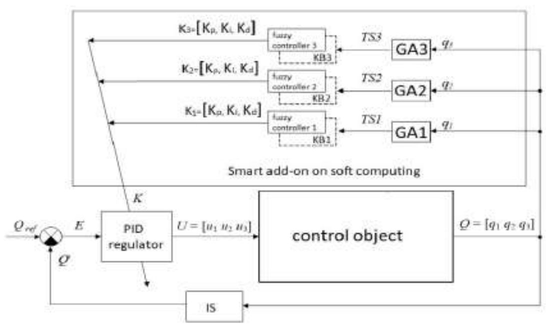

Figure 12. Intelligent control system with separate control for Soft Computing Optimizer of KB for manipulator control with 3DoF

Remark. On Figure 12: K - matrix of proportional, differential and integral coefficients PID-regulator, K_{pi}, K_{di}, K_{ii} , i=1,3 , i - the number of link of the robot manipulator, TS_i - training signal, GA_i - a genetic algorithm that generates a learning signal for design a knowledge base.

Moreover, the knowledge bases themselves, whose responses are used to design robust control, in emergencies may not be robust (imperfect KBs). The scheme for extracting hidden information about the relationships between existing FC (designed using soft computing technologies) for the three links of the manipulator with knowledge base obtained for regular control situations using the quantum fuzzy sensing unit shown on Figure 13 [32].

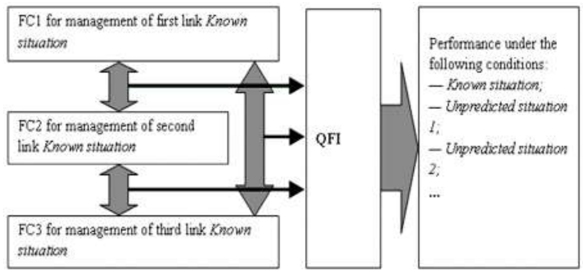

Figure 13. The methodology of extraction of hidden information from relationships between KB, designed for learning control situations

As result of inclusion SCO on soft computing with divided controls of the designed block Quantum fuzzy inference, get a new type of control system - Intelligent Control System Based on Quantum Computing.

The quantum fuzzy inference (see Figure 14) algorithm performs the following sequence of steps:

Step1. Coding.

Step 2. Selection with quantum genetic algorithm (QGA) the type of quantum correlation for constructing control output signals. It is considered spatial, spatio - temporal and temporal correlations (all three types are mixed)

Spatial. Output dependency $K_P^{i\_new}(t), K_D^{i\_new}(t), K_I^{i\_new}(t)$ is determined by the correlation of the following sets of input coefficients:

$$\left\{K_P^1(t), K_P^2(t), K_P^3(t), K_D^1(t), K_D^2(t), K_D^3(t)\right\} \to K_P^{new}(t)$$

$$\left\{K_D^1(t), K_D^2(t), K_D^3(t), K_I^1(t), K_I^2(t), K_I^3(t)\right\} \to K_D^{new}(t),$$

$$\left\{K_I^1(t), K_I^2(t), K_I^3(t), K_P^1(t), K_P^2(t), K_P^3(t)\right\} \to K_I^{new}(t)$$

Where each set is an entangled state:

$$\left|a_1 a_2 a_3 a_4 a_5 a_6\right\rangle = \left|K_P^1(t), K_P^2(t), K_P^3(t), K_D^1(t), K_D^2(t), K_D^3(t)\right\rangle.$$

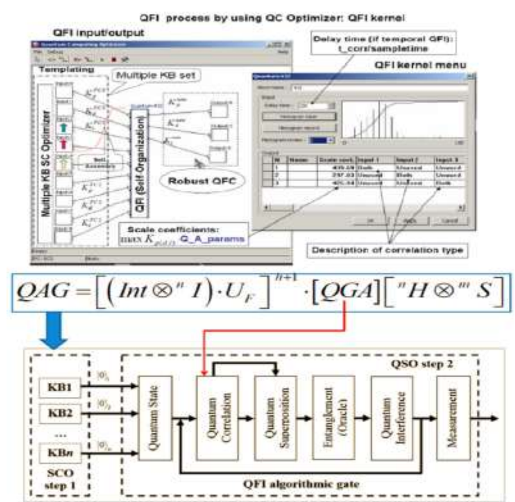

Figure 14. Quantum fuzzy inference algorithm sequence of steps

Spatio - temporal:

$$\left\{K_P^1(t), K_D^1(t-\Delta t), K_P^2(t), K_D^2(t-\Delta t), K_P^3(t), K_D^3(t-\Delta t)\right\} \to K_P^{new}(t)$$
$$\left\{K_D^1(t), K_I^1(t-\Delta t), K_D^2(t), K_I^2(t-\Delta t), K_D^3(t), K_I^3(t-\Delta t)\right\} \to K_D^{new}(t).$$
$$\left\{K_I^1(t), K_P^1(t-\Delta t), K_I^2(t), K_P^2(t-\Delta t), K_I^3(t), K_P^3(t-\Delta t)\right\} \to K_I^{new}(t)$$

Temporal:

$$\left\{K_P^1(t), K_P^2(t), K_P^3(t), K_P^1(t-\Delta t), K_P^2(t-\Delta t), K_P^3(t-\Delta t)\right\} \to K_P^{new}(t)$$
$$\left\{K_D^1(t), K_D^2(t), K_D^3(t), K_D^1(t-\Delta t), K_D^2(t-\Delta t), K_D^3(t-\Delta t)\right\} \to K_D^{new}(t).$$
$$\left\{K_I^1(t), K_I^2(t), K_I^3(t), K_I^1(t-\Delta t), K_I^2(t-\Delta t), K_I^3(t-\Delta t)\right\} \to K_I^{new}(t)$$

Step 3. Building a superposition of entangled states.

Step 4. Intelligent quantum state measurement.

Step 5. Decoding.

Step 6. Denormalization.

The overall assessment of the quality of control is higher in the case of applying the intelligent control systems on the QCO on quantum computing (for all considered types of correlations) compared to the intelligent control systems on the SCO on soft computing with conventional control. Which is a consequence of introducing into the structure of the intelligent control systems an additional quantum fuzzy inference link organizing coordination management. Moreover, if for a robot manipulator with 3 DoF as result of testing *MatLab / Simulink* models, it had the best performance intelligent control systems, using spatio - temporal correlation, then physical testing determined the use of spatial correlation to be the most optimal. For a robot manipulator with 7 DoF, in most cases, spatial correlation was also optimal.

For a robotic arm as robot with 3 DoF, the overall assessment of control quality is improved when using intelligent control systems on QCO with quantum computing compared to using intelligent control systems on SCO on soft computing with one FC. Intelligent control systems on SCO with soft computing with one FC, it is able to solve the positioning problem in the conditions of external unforeseen situations, but it does not always cope with the occurrence of internal unforeseen situations.

Example. On Figures 15 and 16 demonstrated the operation of the manipulator Intelligent Control System (ICS) when using the intelligent control systems on the SCO (on soft computing) and the intelligent control systems on the QCO (on quantum computing) in the conditions of a regular control situation and an external unforeseen control situation (the initial position is changed).

Quantum supremacy. As can be seen from Figures 15 and 16, the intelligent control systems on the QCO (on quantum computing) under the conditions of the considered standard and external unforeseen control situations solves the problem of the exact positioning of the manipulator robot in contrast to the intelligent control systems on the SCO on soft computing.

Let us demonstrate the operation of the intelligent control systems on the SCO on soft computing with divided control in the conditions of an external unforeseen control situation (Figure 17) in comparison with the intelligent control systems in the SCO on quantum computing. As an unforeseen situation is the forced displacement of the second link of 3DOF manipulator.

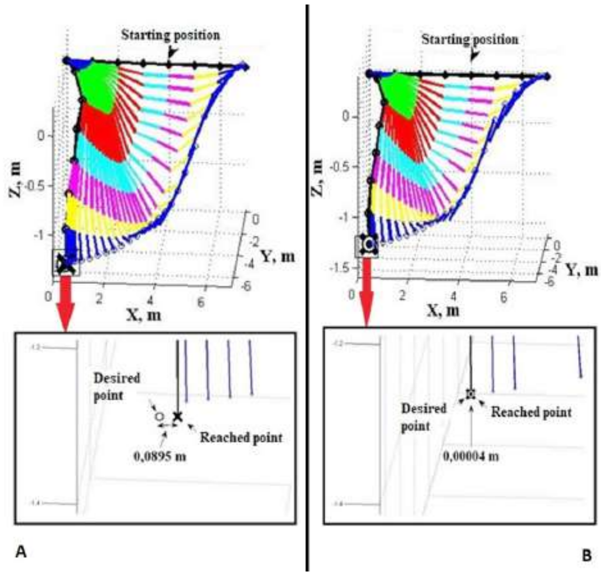

Figure 15. The movement of manipulator in a standard control situation: under control of ICS based on SCO with soft computing (a). ICS based on SCO with quantum computing (b)

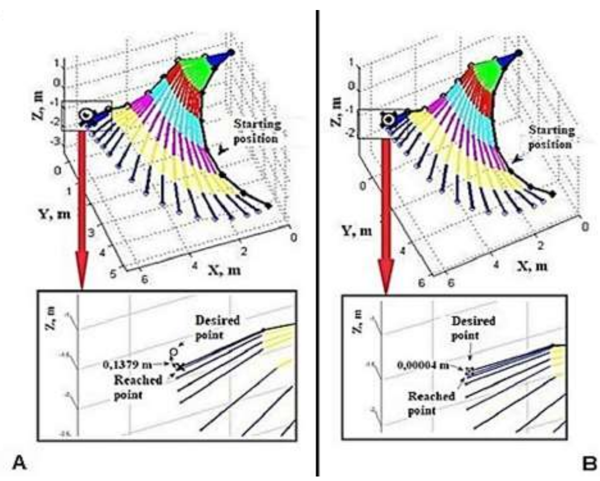

Figure 16. The movement of manipulator in an external unforeseen situation: under control of ICS based on SCO with soft calculations (a). ICS based on SCO with quantum computing (b)

From Figure 17 it is seen that in the considered un-

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foreseen situation, the control of the intelligent control systems on the SCO on quantum computing copes with the task of positioning with a given accuracy, in contrast to the intelligent control systems on the SCO on soft computing with a divided control.

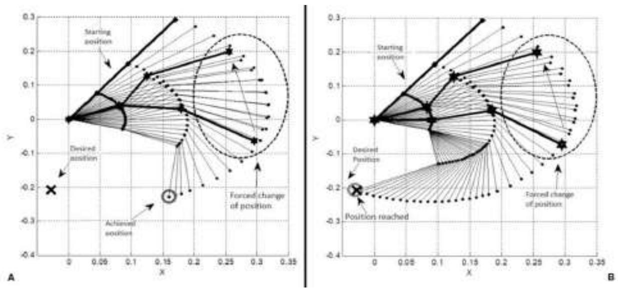

Figure 17. The work of the intelligent control systems on the SCO on soft computing with divided control in an unforeseen control situation (a); intelligent control systems operation on SCO on quantum computing (b)

The inability of the intelligent control system on SCO on soft computing to solve the problem of exact positional control is also illustrated in Figure 18. FC, responsible for managing the second link for the allotted time, was not able to "rehabilitate" after a powerful external impact, as result of which the positioning error of the second link was more than 50 degrees, the control goal was not achieved and the control system as a whole was not robust (Figure 17).

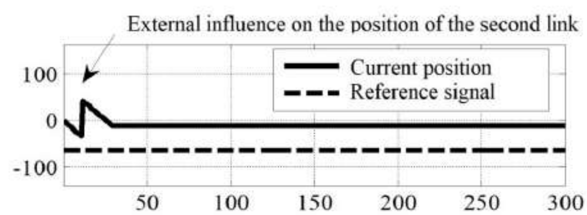

Figure 18. Changing the position of the second link under the control of the intelligent control system on SCO on soft computing with divided control

The results presented on Figures 17 and 18 demonstrated quantum soft computing supremacy in intelligent robust control and can guarantee goal control achievement with required accuracy (in case on Figure 17 the accuracy of control goal achievement achieved more than 120 times).

This result is especially noteworthy in the situation when organizing coordination control due to a single knowledge base (correspondingly using one FC in the intelligent control systems for the SCO on soft computing) the number of input variables. For this case parameters (that determine the functioning of the system) limited by the computing resources of the processor on which the FC is created and the amount of memory in the system in which the FC is located.

Moreover, for complex control objects, such as a robot manipulator with 7DoF, the organization of a single FC is impossible.

In general, the possibility of decomposing the control (dividing one knowledge base into several identical independent knowledge bases) and organizing coordination management by introducing the quantum fuzzy factor link significantly increases the possible number of input variables and thereby expands the possibilities of accounting for the parameters of the system and the control object.

3.1 Information-thermodynamic Analysis of Cognitive Intelligent Control System

The distribution (trade-off) of control qualities determined by the following system of equations:

$$\underbrace{\frac{dV}{dt}}_{Stability} = \underbrace{\sum_{i=1}^{n} q_i \cdot \varphi\left(q,t,k\left(S_O-\left(S_{\mathrm{Tc}}+S_{Cc}\right)\right),u\right)}_{Controllability} + \underbrace{\left(S_O-\left(S_{\mathrm{Tc}}+S_{Cc}\right)\right)\cdot\left(\dot{S}_O-\left(\dot{S}_{\mathrm{Tc}}+\dot{S}_{Cc}\right)\right)}_{Robustness} \le 0 \tag{1}$$

$$\underbrace{\frac{dV}{dt}}_{Stability} = \underbrace{\sum_{i=1}^{n} q_i \cdot \varphi\left(q,t,k\left(H_O-\left(H_{\mathrm{Tc}}+H_{\mathrm{Cc}}\right)\right),u\right)}_{Controllability} + \underbrace{\left(H_O-\left(H_{\mathrm{Tc}}+H_{\mathrm{Cc}}\right)\right)\cdot\left(\dot{H}_O-\left(\dot{H}_{Tc}+\dot{H}_{Cc}\right)\right)}_{Robustness} \le 0 \tag{2}$$

where and means the total thermodynamic and information entropies of the conventional intelligent (Tc) and Cognitive (Cc) controllers, respectively.

It follows from Eq. (1) that the robustness of an intelligent control system can increased by the entropy production of the cognitive controller, which reduces the loss of useful work, and Eq. (2) shows that the negentropy of the cognitive controller reduces the minimum requirements for initial information amount to achieve robustness.

3.2 Information Control Extraction and Action Work

Moreover, information based on knowledge in the knowledge base of the cognitive regulator allows get an additional resource for useful work, which is equivalent to the appearance of a targeted action on the control object to ensure the guaranteed achievement of the control goal.

One of the key tasks of modern robotics is the development of technologies for the cognitive interaction of robotic systems, which allow solving the tasks of intelligent hierarchical management by redistributing knowledge and control functions, for example, traditionally between a leader and a subordinate ("master - slave" system). Modern approaches to solving this problem based on the theory of multi - agent systems, the theory of swarm artificial intelligence, and many others [33 - 35].

Due to the synergetic effect, an additional information resource created and the multi-agent system is able to solve complex dynamic tasks for performing team mutual work. The given task may not fulfill by each element (agent) of the system separately in various environments without external management, control or coordination, however, exchange of knowledge and information allows performing useful teamwork to achieve the management goal under the conditions of uncertainty of the initial information and limited consumption of useful resources.

In particular, it is known that for closed-loop control systems, the amount of useful work W that is extracted satisfies the inequality $W_{\max}(t) = k\int_0^t T_{\min}\dot{I}_c dt' \le kTI_c$, where k is the Boltzmann constant, $T_{\min}(t)$ is interpreted as the lowest achievable temperature by the system in time t for feedback control, assuming $T_{\min}(0) = T$ and I_c determines the amount of Shannon information (entropy transfer) , extracted by the system from the measurement process [36].

Physically, the synergetic effect means the design of knowledge self-organization and the extraction of additional information that allows the multi-agent system to perform the most useful work with a minimum loss of useful resource and with a minimum of the required initial information, and without destroying the lower executive level of the control system.

Together with the information-thermodynamic law of intelligent control (optimal distribution of the management qualities as "stability - controllability - robustness"), an intelligent control system (ICS) is designed with multi-agent systems, ensuring the achievement of the management goal under the conditions of uncertain initial information and limited useful resource [37].

A network of loosely coupled groups of robots working together to solve tasks that go beyond individual capabilities. Different nodes of such a system, as a rule, have a different intelligent level (knowledge, algorithms, and computational bases) and various information resources for design process. Each node should be able to modify its behavior depending on the circumstances, as well as to plan its communication and cooperation strategies with other nodes. Here the indicators of the level of cooperation are the nature of the distribution of tasks, the unification of various information resources and, of course, the possibility of solving a common problem in a bounded time interval.

Example. As noted above, if microscopic degrees of freedom are available to the observer in the form of the Maxwell demon, then the second law of thermodynamics can violated. Szilard showed from an analysis of the Maxwell demon model that work extracted from the thermodynamic cycle in the form as $kT\ln 2$. Moreover, it was shown [38] that recoverable work W_{ext}^S from the system is determined by the amount of information (or quantum-classical mutual information) I, which estimate the extracted knowledge of the system from measurements. At the same time, a similar ratio in the form of a lower boundary exists for the full cost W_{cost}^M measuring and erasing information $W_{ext}^S \le -\Delta F^S + kTI$ and $W_{\text{cost}}^M \ge kTI$, where ΔF^S determines the free energy of the system. Then it is easy to see the speed of the recoverable work $\dot{W}_{ext}$ limited by $\dot{W}_{ext} \le kT\dot{I}$, i.e. limited by the speed of information retrieved [39].

Model of self-organized intelligent control system proposed based on the principles of minimum informational entropy (in the "intelligent" state of control signals) and the generalized thermodynamic measure of entropy production (in the system "control object + regulator"). The main result of the application of the self-organization process is the acquisition of the necessary level of robustness and the flexibility (adaptability) of the reproducible structure.

It has noted that the property of robustness (by its physical nature) acts as an integral part of self-organization, and the required level of robustness in intelligent control system achieved by fulfilling the principle of minimum production of generalized entropy noted above. The principle of minimum entropy production in object control and system control serves as the physical principle of optimal functioning with a minimum consumption of useful work and underlies the development of robust intelligent control system.

This statement is based on the fact that for the general case of controlling dynamic objects, the optimal solution to the finite variational problem of determining the maximum useful work W according to, it is equivalent to solving the final variational problem of finding the minimum of entropy production S. Thus, the study of the

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maximum functional condition $\max_{q_i,u}(W)$ (where q_i, u are the generalized coordinates object control and control signal respectively) is equivalent, the study of the associated problem of minimum entropy production, i.e. $\min_{q_i,u}(S)$.

Therefore, in the developed model, the principle of minimum informational entropy guarantees the necessary condition for self-organization - the minimum of the required initial information in the teaching signals; the thermodynamic criterion of the minimum of a new measure of generalized entropy production provides a sufficient condition for self-organization - the robustness of control processes with a minimum consumption of useful resource.

More significant is the fact that the average amount of work performed by dissipation force $\frac{\langle W_{diss}\rangle}{kT} = S_{KL}\left(P_F \| P_B\right)$, i.e., the work of the dissipation forces is determined by the Kullback - Leibler divergence for probability distributions P_F, P_B. Note that the left side of this relation represents physically thermal energy, and the right side defines purely extracted information about the system.

Information entropy is a measure of the amount of information about the system and the Kullback - Leibler divergence, as well as the determination of the amount of Fisher information.

A similar relationship exists between the work produced by the forces of dissipation and the difference between Renyi [37].

Thus, substituting the relations between the information and the extracted free energy and work in (1) and (2), we obtain the conclusion noted above. Therefore, the robustness of the intelligent control system can increase by the entropy production of the cognitive controller, which reduces the loss of useful resource of the control object; negentropy of the cognitive regulator reduces the requirements for minimum initial information to achieve robustness.

Moreover, the extracted information, based on knowledge in the knowledge base of the cognitive controller, allows getting an additional resource for useful work, which is equivalent to the appearance of a targeted action on the control object to guarantee the achievement of the control goal.

In this Part I of article the solution of intelligent robotic prosthetic arm design is considered.

Remark. This work is a continuation of [40] and based on the concept of an intelligent simulator [41], which includes advanced information technology for the design of intelligent control systems. In contrast to the methodology [14], visual reinforcement of the generation of mental commands is not used in the learning process (the operator is fully concentrated on his own cognitive processes). In particular, the possibility of controlling the prosthetic arm in on line using an electroencephalograph and the corresponding neurointerface software considered.

4. Development of Prosthetic Models

A lot of research has done on prosthetics and the implementation of projects to create new types of limbs.

4.1 Related Prototypes of Prosthetic Arms and Differences from Known Approaches - advantages and Disadvantages

For illustration purposes, Figure 19a shows modern hand prostheses. Figure 19b shows promising interfaces - hands, virtual reality helmet, cognitive helmets.

Remark. Such (and similar) projects have their advantages and disadvantages. Many prostheses don't have feedback from the user (they do not allow him to convey emotional or physiological sensations), cannot be a complete replacement for a lost limb (for example, a long - term phantom of having a healthy limb). Most prostheses are expensive, and their operation and implementation are very costly. They include invasive interfaces and have more features, which, accordingly, affect their cost.

Of the abundance of prostheses presented, three classes can be distinguished: 1) Cosmetic (do not carry any functionality in themselves, only increase the aesthetic level); 2) Mechanical (use the power of levers and rods for movement, which creates some inconvenience in the way they are used); and 3) Bioelectric (have great functionality, but are very expensive and require a constant charge of batteries).

The ability to use 3D printing greatly facilitates the creation of a prosthesis. There are many open resources that provide drawings, sketches, and assembly technologies for various parts and mechanisms, including anthropomorphic parts.

However, the interface development process accompanied by complexity of execution and high cost of such products. An open source project from the Thingiverse [42, 43] website adopted as the basis for a robotic prosthesis with a cognitive control system.

Purpose and goal of Part 1: creation of a model of an anthropomorphic intelligent robotic arm. The work uses the limb of a robot to demonstrate the application of developed technologies. It decided to use the cognitive helmet company EmotivEpoc+ [44] as an interface for recording EEG signals. The combination of these devices creates a software and hardware basis for the laboratory bench of an intelligent robotic simulator.

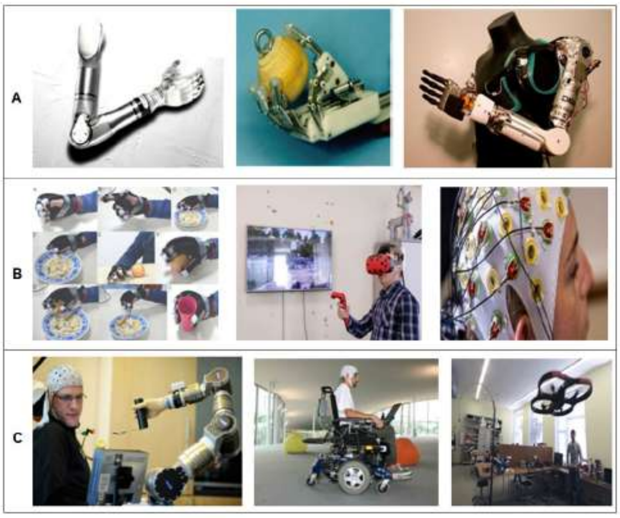

Figure 19. Modern prostheses of hands and hands (a). Computer interfaces in the form of brushes with installed sensors, augmented and virtual reality, cognitive interfaces (b). Examples of application in control tasks (c)

Let us consider in more detail the lower (executive) level of the developed device.

4.2 Prosthesis Manufacturing

The first stage of work is the manufacture of prosthesis parts on a 3D printer. For this purpose, ABS plastic was used (a polymer consisting of acrylonitrile, butadiene, styrene, which, due to its technical characteristics, was widely used as an engineering and structural material in layout engineering) and a 3D printer. The project [42, 43] dedicated to the creation of an anthropomorphic robot was taken as the basis.

Figure 20 illustrates an anthropomorphic robot, sketches of its individual parts and the manufactured part of the project.

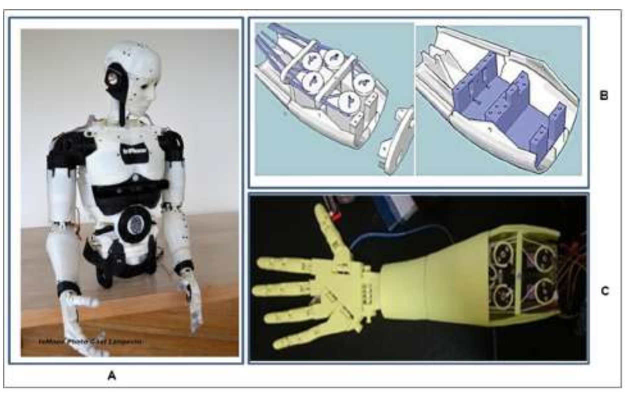

Figure 20. Project to create an anthropomorphic robot (a). Sketches of the robot (b). Manufactured prototype prosthesis (c)

In order to implement a system of mechanical "tendons" that transmit force from "muscle" motors to the limbs (Figure 20b), a nylon thread with a diameter of 2 mm used. Servomotors used as drives, which made it possible to vary the angle of rotation of the output shaft, and then transfer the force with the help of "tendons" to the limbs. Note that it is possible to set the compression ratio of the fingers. The results of the first stage of work (creating a finished prototype) presented in Figure 20c.

To control the servomotors and control the prosthesis itself, a unified Arduino Uno controller based on the ATmega 328 microcontroller used, to control many servomotors, Sensor Shield v 4.0 company Arduino [45] connected to the controller. A schematic diagram of the connection of servomotors shown in Figure 21.

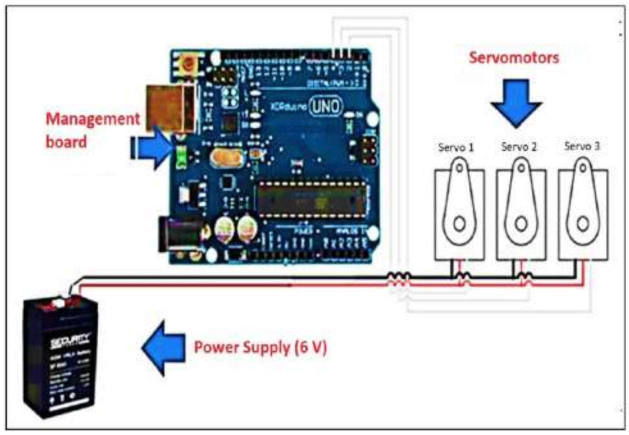

Figure 21. Connection diagram of devices

In this paper, for presenting simplicity of results, the training and operation process performed on a personal computer, and the microcontroller used only to receive and send specific control commands. The implementation scheme presented on Figure 22.

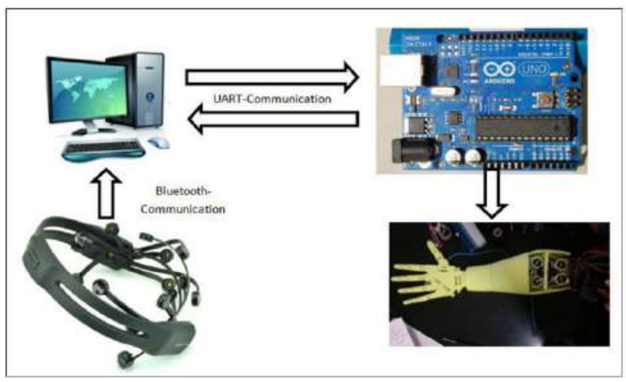

Figure 22. Microcontroller to PC connection diagram

Comment. From the point of view of information technology, it is necessary to take into account the consumption of computing resources in the process of training, updating and operating the device. The rational distribution

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of information-thermodynamic load [46], allows designing the optimal structure of neural networks and integrating quantum cognitive computing on-board processor of the final device. In this case. The processor load in the learning process distributed between the central computer and the controller of the actuator.

4.3 EEG Signal Removal and Data Information Processing

The general concept of using a cognitive simulator is described in [19, 20, 41].

Figure 23a, shows the filtered (refined) with QSCOptKB™ toolkit EEG channel placement on the human scalp.

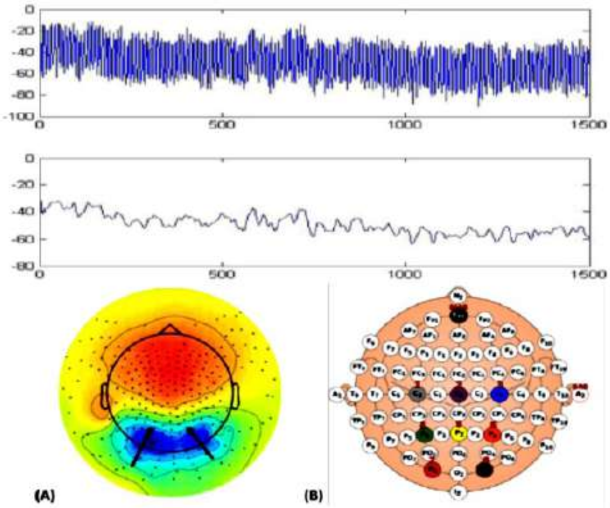

Figure 23. EEG channel placements on the human scalp

Each scalp electrode is located at the brain centers. In 2001 Pfurtscheller identified that many of the neural activity related to fist movements are found in channels C3, C4 and Cz as shown in Figure 23b. F7 is for rational activities, Fz is for intentional and motivational data, P3, P4 and P_z contain perception and differentiation, T3, T4 is for emotional processes, T5, T6 has memory functions and O1 and O2 contain visualization data. In order to remove the noise from the obtained signal, any of the suitable filtering techniques may adopted. Further, the extracted data may move for classification phase.

A well - known marker of cognitive processes is the restructuring of brain rhythms, manifested in a surface-recorded electroencephalogram (EEG) of a person. To signal the brain activity, we used the cognitive helmet company Emotiv EPOC+ (see Figure 25a), and the functional diagram of the software implementation is shown in Figure 24.

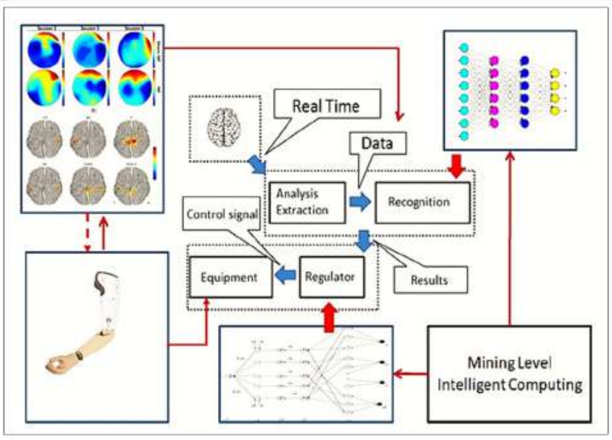

Figure 24. Functional structure of software in on line

In on line, the EEG data received in the block “Analysis of the extracted data”. Then, after filtering and frequency decomposition, the signals enter the recognition unit (see Figure 23). The recognition result is the degree of similarity with previously recorded commands during training. As neural networks, deep machine learning patterns of pattern recognition are used.

Further, when the activation level is exceeded, such signals enter the fuzzy neural network of decision-making, designed using the soft computing optimizer [30, 31]. The output of such a neural network is the target values of the indicators of a managed device. At the same time, the training and operation process is supported by an emotional (positive or negative) reaction of the operator [21], thereby evaluating the quality of training and adaptation of the control system. The design of the “Cognitive Regulator” block based on quantum soft computing optimizer considered in the Part II of this paper.

EPOC has 14 electrodes, which are passive sensors that allow you to register electromagnetic signals. Sensors are mounted on the surface of the skin (non-submersible, non-invasive interface).

Figure 25 b, shows the structure of Emotiv EPOC+ consisting of channels AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (plus CMS/DRL и P3/P4).

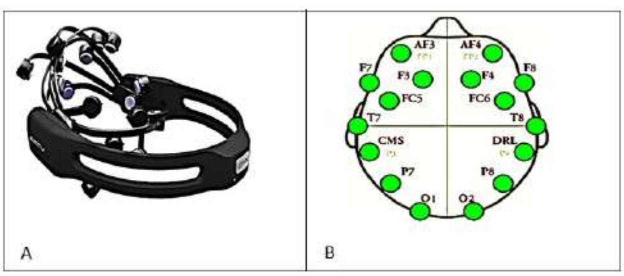

Figure 25. EmotivEPOC+ cognitive helmet(a).The layout of the electrodes of the cognitive helmet Emotiv EPOC+(b)

The supplied software allows receiving, recognizing and recording the EEG signal from the helmet. To analyze the received signal, the so - called EEG frequency rhythms are distinguished.

Remark. The term “frequency rhythm” means a certain type of electrical activity corresponding to a certain state of the brain, for which the boundaries of the frequency range are defined. In the process of cognitive activity, characteristic rhythms of the beta, alpha, theta and delta ranges appear [47] (Figure 26).

The set of simultaneously present rhythms forms a specific spatial-frequency EEG pattern. Patterns are characteristic of different types of cognitive activity and are highly individually specific [15, 19].The ability of an individual to establish rhythmic EEG patterns when performing certain cognitive tasks makes up an “encephalographic” portrait of his personality.

Comment. One of the main components of cognitive neurointerface technology is gaming simulators. It is important to note that during training, the control model acts as a system model on the monitor screen. This, in turn, allows not only to train the brain to generate mental commands, but also to tune the control system of the control object itself, adjusting it to the operator, thereby ensuring increase of overall performance in the system “brain - computer”. This kind of feature is because when a person works with a cognitive helmet, the program adapts to the characteristics of the operator, adjusting the control system. Developers of such equipment with the level of operator training to generate various mental commands usually associate the quality of team recognition.

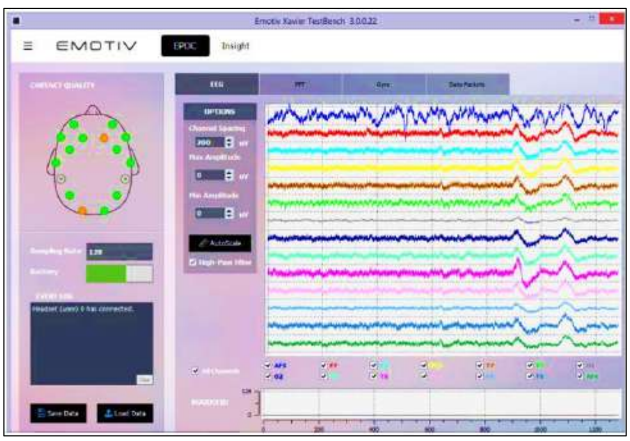

Figure 26. EEG frequency rhythms

The software bundle provides specialized games - simulators, in which the learning and training process takes place. Typically, computer games used for this, where the operator must perform an action that can matched with some command used to control the object. When playing, the operator develops his skill in working with a helmet, which subsequently makes it possible to control real technical devices (manipulators, wheelchairs, and other devices). Training can be either active, with external stimuli (for example, light of a certain frequency, video and audio material, pictures, etc.), or passive if the operator presents it without external influence during the generation of a mental command.

Also, additional hardware, such as a virtual reality helmet, which will visualize the user’s actions in the virtual world, thereby increasing the effectiveness of training, can be used to form a user with a more complete picture of learning. The duration of training and the intensity of training affects the quality and number of recognized mental teams. If the first time a person can learn how to generate signals in the brain for one team, then for good recognition of two or more teams, several exercises are necessary.

Accordingly, both the psychophysiological characteristics of a person’s state (including his position in space) and his level of training will influence the management system and the achievement of the management goal. Usually (according to information from the manufacturer) for the system to work well using four teams. It is necessary to conduct regular training for 2-3 weeks, and after training the operator experiences fatigue. And accordingly, time is required to restore strength. The learning process described in more detail in [37, 45]. A program based on the Epoc cognitive helmet SDK written to control the prosthesis servomotors.

The learning process consists of two main blocks: (1) analysis of electroencephalographic indications and identification of frequency patterns specific to a particular operator; (2) generating and recording mental commands.

At the training stage, using the wet non-immersed brain-computer interface with passive electrodes of EmotivEpoc+, the activity of certain parts of the operator’s brain recorded. Initially, it is necessary to obtain a frequency slice of the operator’s neutral state (the operator is at rest), this frequency slice is necessary to improve detection of the nervous excitation of the operator during further analysis.

In the future, to generate mental commands, the operator for a certain period of time (8 seconds) mentally models the necessary action, which will serve as the basis of the mental command (contraction, relaxation of various muscle groups, etc.). And also at this moment performs this action with «Live» hand. An individual signal recorded for each mental command.

From the viewpoint of the control system, the operator must be able to re-generate the recorded signals, which

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interpreted by the system to control the movement of the device. The frequency rhythm shown in Figure 27.

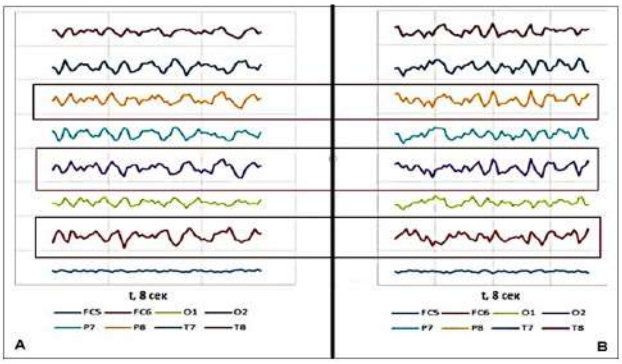

Figure 27. Frequency rhythm of the neutral state (a) and the state of excitation (b)

Typically, statistical methods used to evaluate and recognize signals, including the calculation of variance and mathematical expectation.

Figure 28 demonstrate highlights the most different signals from each other, which the operator associates with a mental command and a neutral state.

FC5	FC6	O1	O2	P7	P8	T7	T8	
126,66	3459,63	2108,80	3791,51	2940,07	3757,97	3768,52	2523,59	Neutral state
103,47	4201,47	1644,94	3894,85	3072,52	3129,58	3455,78	1613,89	Excitation state

Figure 28. Dispersion of mental command signals

Dispersion of signals generated by the operator is a fairly simple and effective method for comparing signals of mental commands. Additional various methods described in [47].

Figure 29 shows the interface of software tools that allows you to receive and process data from the brain-computer interface of EmotivEpoc+ (the program code created in the C# programming language using the Windows Forms graphical interface).

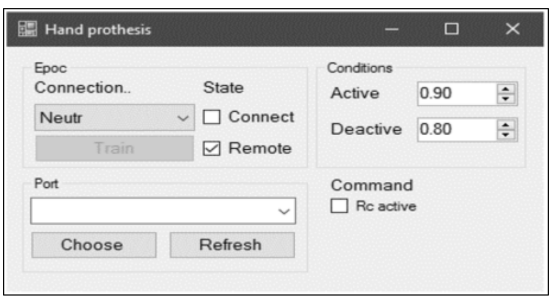

Figure 29. Program interface

Data exchange between the cognitive helmet and the computing center done using the Bluetooth protocol stack, as well as the UART protocol. To initialize a cognitive helmet, it is necessary to mark the "Connect" field, then select a mental command from the drop-down list or create a new one. Now of pressing the "Train" button, the operator begins active cognitive activity associated with the selected team. After completing the training process, it is necessary to save the obtained data, connect the prosthesis to the computer, set the boundaries for activating the mental command. And then put the application into the prosthesis control mode (by marking the "Rcactive" field). When click on the "Train" button, information sent to the helmet about the currently selected mental team for training, after which some time activity indicators of the human brain recorded. When the helmet fixes similar parameters of mental activity, the key of the current team will change from neutral to the team associated with these parameters.

In addition to connecting directly to the helmet and prosthesis, it is possible to test the program using the third-party program Emotiv Xavier Composer, which simulates the work of a cognitive helmet and allows sending virtual mental commands to the application. In the program code, this implemented as a call to the Remote Connector Connect methods.

If the user sends a mental command to the program, then the spatial-frequency pattern evaluated, after the scaling of the received signal relative to the set minimum and maximum, the corresponding signal sent to the COM port. The following event occurs when the timer is started, which starts to control the prosthesis during the connection of the cognitive helmet, which is shown on the main screen.

Comment. The variable "power" is the power of mental effort. Since the prosthesis has physical limitations during operation (it is not possible to send servomotors an angle of rotation that extends beyond the interval [0.180]), the variable "a" trimmed in possible values to the boundaries of this interval. In the program code, the second possible value is another such construct. Thus, a binary tree implemented. After the operations performed, a line of the form "a A" is sent to the COM port, where "A" is the angle from 0 to 180, by which all five servomotors will be rotated, taking into account the physical restrictions previously established in the Arduino program for each one in particular. Such methods prevent possible damage to the prosthesis if the commands coming from the helmet are misinterpreted.

Figure 30 shows a graph showing the frequency rhythm of the operator. The trained cognitive control system, analyzing this frequency pattern, recognizes the mental commands present in the frequency rhythm.

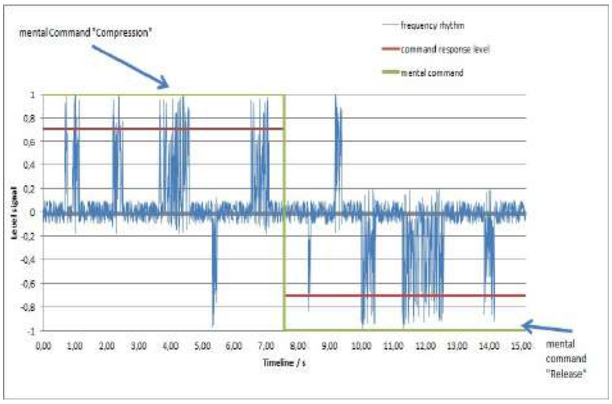

Figure 30. Execution of mental commands

Figure 31 shows a graph showing the registration of mental commands at discrete time intervals.

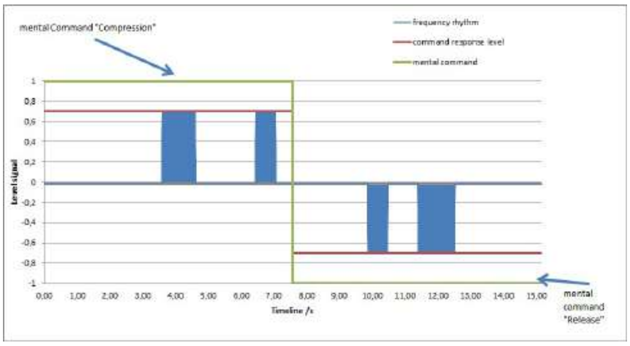

Figure 31. Regulatory signaling for the actuator

Figure 32 shows the process of the experiment.

Figure 32. Conducting an experiment: execution of the "unload" command (a), the execution of the command "compression" (b)

The operator, using mental commands that read by the EPOC+ cognitive interface, controls the compression-unloading process of the prosthesis brush.

In accordance with the scheme shown in Figure 10, EmotivEpoc in on line captures the excitations of the cerebral cortex at the time of a certain cognitive activity (generation of mental command). The received data goes to the computer center, where they are recognized. Based on the analysis of the obtained frequency pattern and estimation of the signal level at a discrete time instant, a control action generated for the actuator.

This experiment demonstrates the possibilities of sharing electromechanical, anthropomorphic devices of a modern class of computer neurointerfaces and software, which in turn is one of the strongest incentives for the development of end-to-end digital information technologies of "strong" artificial intelligence and intelligent assistants of service use.

5. Conclusion

(1) This work (the first part) presents the development of several high-tech areas of robotics, which have practical scientific and technical interest, both in separate and in joint developments.

(2) It has been shown that the prospect of developing cognitive intellectual control using soft and quantum computing technologies is one of the important tasks in creating a robotic prosthetic arm, such as a simple case of a robot avatar, and is integral to the development of information technology in the framework of the concept of an intelligent simulator [41].

(3) The use of expert recommendation systems with a deep representation of knowledge [6,7] and quantum end-to-end technologies of deep machine learning with quantum EEG processing [17,49] allows the appointment, selection of control of robotic prostheses of the hand, taking into account the individual psychophysiological characteristics of the patient and the operating environment.

(4) On the one hand, these products if properly developed can presented on the market of commercially attractive products, on the other hand, technologies for using new types of intelligent information technologies and human-machine cognitive interfaces.

(5) The next stage of development is the creation of a cognitive intellectual control system for a robotic arm-prosthesis for maintenance based on IT quantum soft computing, quantum EEG processing filters [17] and Kansei / Affective Engineering intelligent computing technologies with an assessment of the user's emotional state [49 - 51].

(6) The work, in its essence, reflects the completeness of the formation of a new educational approach in intelligent robotics [32, 40, 41, 52] - a hybrid cognitive intelligent robotics based on neural interfaces with new types of IT data processing.

Appendix 1. Contemporary models of affect, motivation, emotion and cognitive control for Kansei /Kawaii / Affective Engineering

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

Example. 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

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of the brain (Figure 33a). Early research suggested that the rostral cingulate cortex (Brodmann's 'precingulate'; architectonic areas) plays a key part in affect and motivation (Figure 33b). 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 [22].

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 Figure 33d.

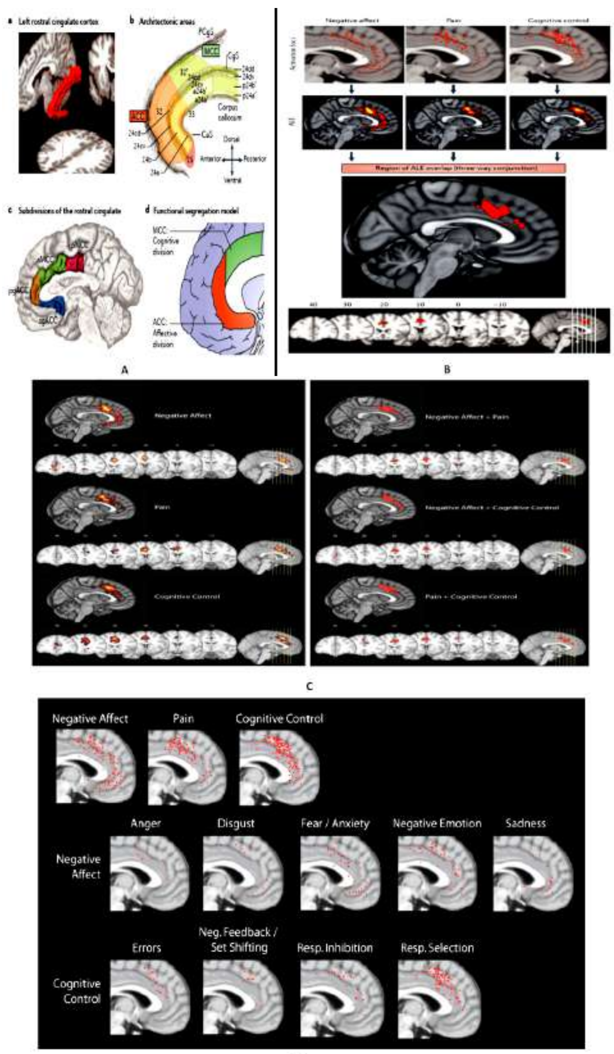

Figure 33. (a) - Divisions of the human rostral cingulate cortex; (b) - Negative affect, pain and cognitive control activate a common region within the anterior subdivision of the midcingulate cortex - aMCC (The map depicts the results of a coordinate-based meta-analysis (CBMA) of 380 activation foci 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 conjuction maps; (d) - Activation foci maps [22]

Example: *Emotional learning occurs mainly in the amygdala*. The system operation consists of two levels: the amygdale 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 Figure 34, the system on Figure 34a, consists of four main parts [54]. 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).

For each Anode 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 Figure 34a). The E node sums the outputs from A except for the A_{th} and then subtracts the inhibitory outputs from the O nodes. The result is the output from the model.

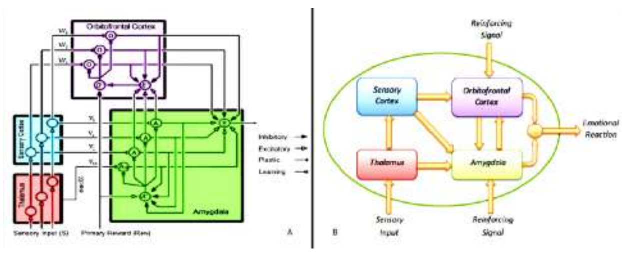

Figure 34. Graphical depiction of the brain emotional learning process (a) and the process of generating emotional reactions in the limbic part of human brain (b)

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.

Example. Let us consider briefly Brain Emotional

Learning Based Intelligent Controller (BELBIC) structure [53]. 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 Figure 34b). A control system strategy, based on brain emotional learning, was proposed by Caro Lucas in the early 2000s (Lucas et al., 2004). The limbic model used was based on the neural link, between the amygdale and the orbitofrontal cortex, proposed by Balkenius and Moren. This control paradigm is commonly designated by BELBIC which stands for brain emotional learning based intelligent control. The reasoning behind the integration of the limbic model into a closed loop control system can be tracked down to the seemingly robust way that the brain performs decision making. Actually, control has all to do with decision making: the controller goal is to devise the best input actions based on the incoming information according to the system states. These actions can be taken considering the past, the present or even forecasts on the future system states. Hence the controller produces a mapping between its input signals and the output control signals by means of an arbitrary decision function which can be described by means of differential equations, as in PID-controllers, or by an inference mechanism such as in Fuzzy or Neuro-Fuzzy control. Alternatively, it can be based on the result of the optimization of a cost function such as linear quadratic regulators (LQR) or model predictive control (MPC). In the BELBIC control system architecture this input-to-output transformation is imposed by means of the limbic system model. In this case, both the external stimuli and reward signals are generated in such a way as to produce a closed loop system response according to some target characteristics. In addition, due to the recursive nature of the weights update law, this controller is able to gradually learn how to handle changes in the system dynamics. A key point in BELBIC is the external stimulus and reward signals definition.

Notice that there are not universal rules to carry out this task. This choice is flexible and must be custom defined according to the end application. For example in Lucas et al. the reward signal $r(t)$ is obtained as a weighted sum of the error signal and the control effort and the external stimulus signal $i(t)$ is defined as a linear combination of the system output and its first derivative.

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 feedforward control 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.

Reza Keramat et al. [54] consider that in practical systems important information originates from two sources. One of the sources is the experts, who define their knowledge of the system using the natural language. The other consists of measurements and mathematical models derived from physical laws. Hence, what matters is how to incorporate these types of information into the design of systems. The question is that how it is possible to formulate human knowledge within a framework similar to mathematical models.

Basically, the main function of a fuzzy system is to make such a conversion possible. Fuzzy systems are based on knowledge or rules. The core of a fuzzy system is a knowledge base following the IF-THEN fuzzy rules. If a fuzzy system is used by a controller, the controller is called "fuzzy controller".

The fuzzy controller designed for the full bridge DC-DC converter takes two inputs: error (e) and error variations (Δe). The membership input functions for this controller are in the range of (-5, 5). Membership functions for each of the two input components of error and error variations are shown in Figure 35.

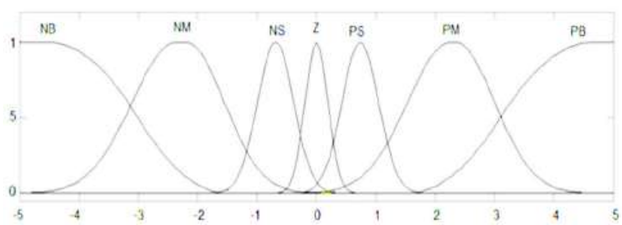

Figure 35. The membership functions for e and Δe

Seven membership functions are used here for the input: negative big (NB), negative medium (NM), negative small (NS), zero (Z), positive big (PB), positive medium

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(PM), and positive small (PS). The controller output is assumed to be equal to the duty cycle, which varies between 0 and 0.5. Figure 36 displays the controller output functions.

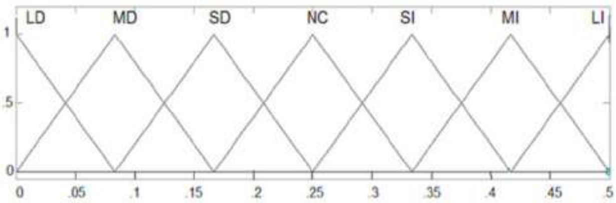

Figure 36. The output membership functions

Reza Keramat et al. show the effectiveness of BELBIC for the full bridge DC-DC converter. Figure 37 shows the system output voltage after the application of the fuzzy and BELBIC controllers.

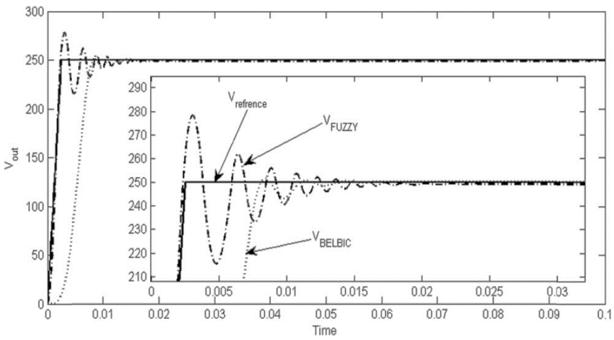

Figure 37. The comparison of the fuzzy controller with the BELBIC

As seen in this figure, the BELBIC has a slight overshoot while the fuzzy controller has a considerable overshoot (the initial overshoot is 35 V). The time required for stabilization is almost the same in both cases. It is therefore concluded that the BELBIC outperforms the fuzzy controller.

In Reza Keramat's experiment the BELBIC controller outperforms the fuzzy controller. Considering the uncertainty of system parameters (including inductance, capacitance, and input voltage and acceptable variations of load), the BELBIC presents better performance than the fuzzy controller. Although fuzzy control is a robust and effective method for a large number of engineering systems, but its design (and consequently its performance) is almost depend on the experience and tact of the designer. Furthermore, after design and installation, its performance is not improved, and in other word, it is not a learning-based or intelligent controller.

It can be stated that a Learning Based Intelligent Control which "may" in the first step, act not as satisfying as any another modern controller, any straight-forward-designed controller after few iterations thanks to its learning automata feature. Based on this deduction, we felt no need to emphasize the comparison of these controllers after setting optimization.

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