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ARTICLE

Intelligent Control of Mobile Robot with Redundant Manipulator & Stereovision: Quantum / Soft Computing Toolkit

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ABSTRACT

The task of an intelligent control system design applying soft and quantum computational intelligence technologies discussed. An example of a control object as a mobile robot with redundant robotic manipulator and stereovision introduced. Design of robust knowledge bases is performed using a developed computational intelligence - quantum/soft computing toolkit (QC/SCOptKB™). The knowledge base self-organization process of fuzzy homogeneous regulators through the application of end-to-end IT of quantum computing described. The coordination control between the mobile robot and redundant manipulator with stereovision based on soft computing described. The general design methodology of a generalizing control unit based on the physical laws of quantum computing (quantum information-thermodynamic trade-off of control quality distribution and knowledge base self-organization goal) is considered. The modernization of the pattern recognition system based on stereo vision technology presented. The effectiveness of the proposed methodology is demonstrated in comparison with the structures of control systems based on soft computing for unforeseen control situations with sensor system. The main objective of this article is to demonstrate the advantages of the approach based on quantum/soft computing.

1. Introduction

The application of robotic systems in various problem-oriented domains gives a significant positive effect; moreover, not only industrial intelligent robots, but also robots for service use with various degrees of social responsibility (medical robots, rescue robots etc.) are spreading [1-3]. The effectiveness of such robot's application directly depends on the quality of control systems [3], which are the most labor-intensive part of the robotic complex. The prototype presented below is used in the education process, the software component of each block of the control system is modernized through the application of soft and quantum computing IT. A significant increase in robustness [4] when using these types of computing allows us to say that the creation of an effective robust and adaptive control system for robotic devices requires an additional software and algorithmic support platform in the form of sophisticated toolkit based on soft and quantum computing (***Quantum computational intelligence toolkit***) [4]. Specialists in

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the design and development of various robots rely on an intelligent platform for the application of computational intelligence technologies. This approach allows unifying the process of intellectualization of the created hybrid industrial service and special purpose robots [1-3].

In the article we are focused the attention on the fact that the application of quantum computing in the design process of intelligent control systems (ICS) significantly increases the reliability of hybrid intelligent controllers by introducing knowledge self-organization capability. The basic principles of creating robust knowledge bases (KB) are described. The paper describes an experiment, the results of which make it clear that the effectiveness of a fuzzy controller is significantly reduced in case of emergency situations. We propose an approach that allows to solve a similar problem by introducing a quantum generalization of strategies in fuzzy inference in online from a set of pre-defined fuzzy controllers (FC) by new ***Quantum Fuzzy Inference*** (QFI). We consider a new structure of intelligent control system (ICS) with a quantum KB self-organization based on QFI. We especially focus on ***robustness of control*** because it is the background for support the reliability of advanced control accuracy in uncertainty environments. The main goal of this work is to provide a brief description of soft computing tools for designing independent FC, then we will provide the QFI methodology of quantum KB self-organization in unforeseen situations. Quantum supremacy of classical intelligent control system design in unexpected control situations demonstrated.

1.1 State of Art of Robotic Systems Development

The basis of the intelligent robot control system is to achieve a synergistic effect from the interaction of various on-board robot systems (a movement system, a mobile manipulator control system, an image processing system etc.). This approach was identified and supported by research and development in Japan in the mid-90s of the last century [1-3]. It should be noted that now this particular approach is fundamental in robotics.

In particular case, in [1-3] is described how the mobile robot for service use works in buildings with different scenes of rooms and moves in unstructured environments in presence of many human being operators and unexpected obstacles applied cognitive graphic of path planning and soft computing for control of different technological operations (open door, getting on an elevator, room control operations and so on). It was suggested to construct a simulation system for mobile service robot behavior based on cognitive graphics with virtual and complimentary reality. This system is used for possible world's simulation in the robot artificial life. This allows us to evaluate the control algorithms in online 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 technology. A new form of direct human - robot communications (including emotion, instinct and intuition) and an autonomous locomotion control system were developed (see Figure 1). Authors considered direct human-robot communications based on natural language (NL) and construct the simulation system of spatial scenes and robot behavior in virtual reality (VR).

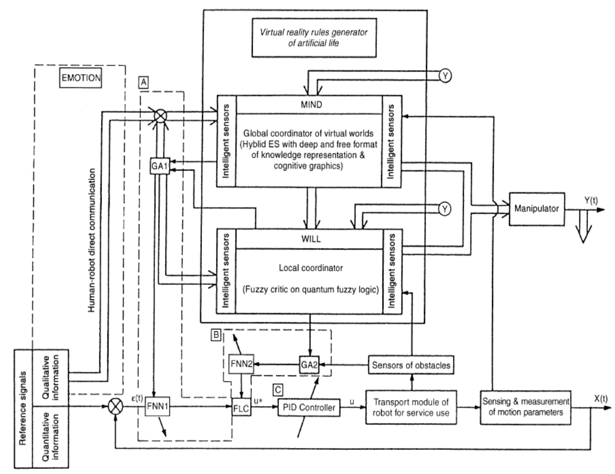

Figure 1. Structure of Artificial Intelligence (AI) control system with distributed knowledge representation (on control signal levels). a - Intelligent control "in large" b - Intelligent control "in small" c - Control on executive level

It was 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. Also, three sub-systems which organize the service robot system for its autonomous navigation and these soft computing are described in [3,5]. 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, fuzzy neural networks (FNN) and genetic algorithm (GA). Experimental results on the developed robot show that the proposed methods are very useful for autonomous locomotion control of the robot.

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Example. Intelligent control and soft computing for avoidance of obstacles and execution of technology operations - 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. In process of robot's locomotion from point to point mobile robot must avoid obstacles in room, and achieve starting position for successful opening room door (as technology operation from one point to another point) and go out the room to elevator in presence of obstacles in a corridor. Movement process is planned by the managing system which was described in [5].

It must be said that the management of poorly formalized and poorly structured control objects (CO) with a variable and complex structure, variable parameters and uncertain operating conditions, in a group or an autonomous object requires the use of end-to-end (in the general case - quantum) information technologies. Studying the problems of implementing control systems for such new and extremely complex CO as NICA, LHC, data processing of telescopes, autopilots, objects of intelligent robotics indicates a significant dependence of the robustness of the system on the embedded computing basis of the most ICS [6]. It is necessary to revise the science platform that is embedded in end-to-end information technology (IT) for the design of ICS.

Traditional modern automatic control systems fundamentally do not take into account the occurrence of contingency management situations and do not include the human being cognitive factor in the control loop, which does not guarantee the timely achievement of the management goal - obtaining the maximum intensity of functioning and stable repetition of the required operating modes with minimal cost of useful resources, such as: time settings, power consumption and more other. In the conditions of uncertainty or inaccuracy (imperfect) of the initial information, unforeseen situations or information risk, the traditional (using the principle of global negative feedback) and widely used in industry PID-controller often does not cope with the management task. At the same time, the solution to the problem of global robustness of the PID-controller is still unknown, despite the relevance of this problem.

Remark. Systems based on biological systems and mimicking their working conditions and behavior are found to be more adaptive and systematically. Their responses are faster and more accurate as compared to the conventional systems. The major drawbacks found while dealing with the static controllers like PI, PID etc. are that they are less efficient for dealing with the complexities and non-linear disturbances. Also, they are non-adaptive and less robust. However, the computational model based on the mammalian decision system could deal with these complexities and non-linearity more ideally and robustly. In online process control systems, all the conditions are uncertain. Also, some complex processes are very dynamic and conditionals are not known with accurate precisions. Thus, in these systems, the design of the controller is very crucial. Also, solving this non-linearity through conventional computational model proves to be very slow. Also, in online scenarios the disturbance sources are unknown and thus any prior model cannot be predicted. Adaptive models are required for dealing such scenarios. Thus, various AI techniques like neuro-fuzzy techniques, Genetic Algorithms, PSO are proved. A model based on limbic-system of mammalian brain emotions has been proposed by Caro Lucas in 2004 [7]. He has demonstrated that emotion-based decisions are quick and more satisfying all the constraints. He has proposed the model based on dynamic limbic system of brain of mammalian. A BELBIC model presents the mimics of the limbic systems components - amygdala, orbito-frontal cortex, thalamus, sensory cortex. It has been implemented for various SISO, MIMO, and other non-linear systems. Various results have demonstrated its very fast control action, better disturbance handling capacity, and robustness (see Appendix 1).

This is also due to the fact that the classical methods of control theory have synthesis and design methods for well-formalized, well-defined and well-described CO that operate in previously known conditions and situations. However, unforeseen circumstances and their individual characteristics determine the secrecy and underdetermination of the parameters of physical and mathematical models, and should be taken into account in the KB of intelligent FC. Quantum end-to-end IT allows designing hierarchical ICS's, which make possible to redistribute the degree of decision-making responsibility between ICS's depending on a dynamically changing situation [6,8].

This article also provides a brief description of the developed system of pattern recognition, which is based on stereovision technology. The use of stereovision allows obtaining data of the depth of the image, the distance to objects, provides an opportunity to build a 3Dpicture of the surrounding world. This article discusses the architecture of convolutional neural networks and its application in intelligent robotics. Advantages of convolutional networks are used for recognition with a high degree of invariance to transformations, distortions and scaling. The convolutional neural network is a widespread and effective tool for deep machine learning, with the help of which computer vision problems are successfully solved. The process of classifying images of a convolutional neural network is close to a similar process occurring in the cortex of the human brain. This paper presents a brief description of the modernization of the pattern recognition system based on stereo vision technology.

1.2 IT for the Design of Robust Intelligent Control Systems

The use of FC in conjunction with the PID-controller led to the creation of hybrid fuzzy ICS with various levels of intelligence depending on the completeness and correctness of the designed KB. The use of soft computing technology (based on GA and FNN) has expanded the field of effective application of FC by adding new functions in the form of learning and adaptation.

The developed technology and intelligent tools Soft Computing Optimizer (SCO &IICS) SCOptKB™ made it possible to design robust KB based on the solution of one of the algorithmically difficult problems of the theory of artificial intelligence - the extraction, processing and formation of objective knowledge without expert estimates. Three GA's are used in this SCO, which allow us to design the optimal FC structure (type and number of Membership function (MF), their parameters, number of fuzzy inference rules), which approximates the training (learning) signal with the required error. In this case, the optimal FNN structure is automatically designed and a universal approximator model is formed in the form of FC with a finite number of production rules in KB [8].

The technology uses new types of computational intelligence (see Figure 2). The design process for robust KB consists of two interconnected stages based on soft and quantum computing. Design is carried out on the basis of Computational Intelligence Toolkits - SCO & QCO (QC/SCOptKB™).

At the first stage of the design process individual KB's are formed for two (or more) FC's, which operating in specific learning control situations. At this stage an evolutionary multi-criteria GA with soft computing technology and fuzzy stochastic modeling is used. The mathematical model of the system and the CO (functioning in conditions of training with reinforcement), according to the measured output signals of sensors and control actions, can act as an information source of the design process.

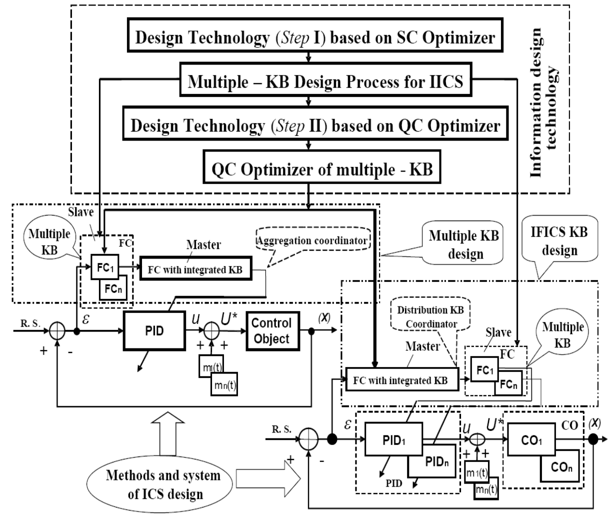

Figure 2. Structure of information design technology of IFICS

From the point of view of hierarchical multi-agent management, the developed IT allows managing both autonomous objects and hierarchically structurally connected teams of autonomous robots (Multiple KB design in Figure 2). On Figure 2 is presented the information design technology of robust integrated fuzzy intelligent control systems (IFICS). Main problem in this technology is the design of robust KB of FC that can include the self-organization of knowledge in unpredicted control situations. The background of this design processes is KB optimizer based on quantum/soft computing [9]. Concrete industrial Benchmarks (as "cart - pole" system, robotic unicycle, robotic motorcycle, mobile robot for service use, semi-active car suspension system etc. [5,10-13]) are tested successfully with the developed design technology.

2. Unconventional Computational Intelligence Toolkit: Soft and Quantum Computing Technologies

Soft computing and quantum computing are new types of unconventional computational intelligence toolkit (details see in http://www.qcoptimizer.com). Technology of soft computing is based on GA, FNN and fuzzy logic inference. Quantum computational intelligence is used quantum genetic search algorithm, quantum neural network and QFI. These algorithms are including three main operators. In GA selection, crossover and mutation operators are used; in quantum search algorithm superposition, entanglement and interference are applied.

On Figure 3 is presented the structure of robust intelligent control system in unpredicted control situations. This structure is the particular case of general structure of

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IFICS (see Figure 2).

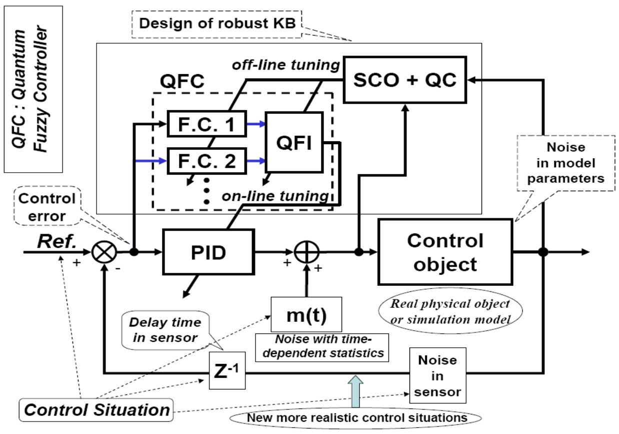

Figure 3. Structure of robust intelligent control system in unpredicted control situations

Remark. An application of developed toolkit in design of "Hu-Machine technology" based on Kansei Engineering is demonstrated for emotion generating enterprise (purpose of enterprise). We are considered the humanized technology of intelligent robotic systems design based on Kansei Engineering and Quantum/Soft Computing [14]. As well known the subject of humanized technology or human-related systems has been actively researched. With the increasing concern regarding human factors in system development Kansei Engineering and Soft Computing are the most representative research fields on this subject. Soft computing toolkit is developed for *emotion*, *instinct*, and *intuition* recognition and *expression* generation. In particular, with GA (as effective random search of solution) an intuition process is modeled. FNN is used for description of instinct process that modeled approximation of optimal solution in unpredicted control situation. Fuzzy logic control is used for design of emotion according to corresponding look-up table. Quantum computing toolkit is used for increasing of robustness in intelligent control systems based on superposition and correlations of affective operations. Detail description of quantum computing toolkit and QFI are described in [8]. Results of simulations [4,8] are shown that from two unstable fuzzy controllers it is possible to design in online a new robust fuzzy controller. It is a pure quantum effect and do not have a classical analogy [15]. These results of quantum game simulation show that the winner is quantum fuzzy controller (QFC) designed from two imperfect 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 ICSs). Also, important the new result for advanced control system that all other controllers (FC1, FC2) are failed but QFC is designed in online a new FC with increasing robustness. This approach was applied to other complex robotic systems [11-13].

2.1 Structure and Main Functions of SCO

As above mentioned in ICS design soft computing technology is a combination of the following approaches: fuzzy systems theory, GA and FNN. FC is the central element of ICS and generates time-dependent control signals (control laws) with gain k_p, k_d, k_i (coefficient gain's schedule) of the PID-controller.ICS structure with FC and SCO blocks in soft computing simultaneously includes the following management qualities: controllability, precision accuracy and stability (lower control level - ACS), learning and adaptation (upper intelligent control level - FC with robust KB in learning control situation). Fuzzy controller is the universal approximator with bounded set of production logic inference rules (look-up table). In the case of approximating a certain control signal, the input components can be a control error, the error integral and its derivative, and the output component can be the required value of the control action or adjustable parameters of the control system, for example, the coefficient gains of the PID controller. The result of the approximation of the learning signal is the designed KB for FC, including the optimal finite set of production rules and optimally formed parameters of the membership function of the input and output variables of FC.

The developed technology supports a software client-server architecture with remote configuration and transfer of KB, which allows the CO to receive KB from the SCO unit or from other CO's remotely, this makes it possible to remotely control structurally new objects, such as swarm of robots, multi-agent systems, complex distributed automated production, physical installations such as Mega-Science. In addition, this technology makes it possible to accumulate (and later to acquire new knowledge), update and adapt KB for a specific CO and control situation (including emergency) in online. The result of the toolkit application at the first stage of the ICS design process is the required type of universal approximator in the form of FC with optimal KB structure (see Figure 2).

2.2 Structure and Main Functions of QFI

The purpose of applying quantum computing and creating a self-organizing quantum controller is to combine the intelligent controllers of various sensors obtained in the first stage into a self-organizing connected multi-agent network based on a quantum controller and cognitive-in-

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formation interaction between KBs. Quantum computing technologies for creating self-organizing KB intelligent regulators are considered in [16,17]. In [16] a new type of quantum search algorithm on the generalized space KB of FC was described (KB designed on the basis of soft computing technologies). The QFI model implements the self-organization of KB, based on the physical laws of the theory of quantum computing [18,19] and the application of four operators: superposition, quantum correlation, interference, and measurement. The first three are unitary, reversible quantum operators, and the fourth (measurement operator) is classical (irreversible).

The QFI design process includes the design of a quantum algorithmic gate - the matrix form of three quantum operators: superposition, entanglement and interference, which are part of the structure of quantum search algorithms, and a source of quantum information that is a hidden variable in classical states. The main unit of such ICS is the quantum genetic search algorithm (QGSA). QFI operators can be implemented both on a quantum and on a classical processor, which in the second case allows you to integrate them into various control systems and built-in intelligent controllers, taking into account the limitations of the computing resource of the elements of an experimental laboratory bench or on-board system. The very process of creating such an algorithmic gate requires the attraction of large computational resources, in connection with which a methodology has been developed for processing big data and conducting quantum computing on a supercomputer (for example, "Govorun" LIT JINR).

The QFI algorithm (see Figure 4) for determining new control parameters (a special case of implementing quantum computing on a classical processor) consists of such stages as normalization, formation of a quantum bit, after which the optimal structure of the quantum algorithmic gate is selected, and the state with maximum amplitude is selected probability, and decoding the signal to obtain new control parameters.

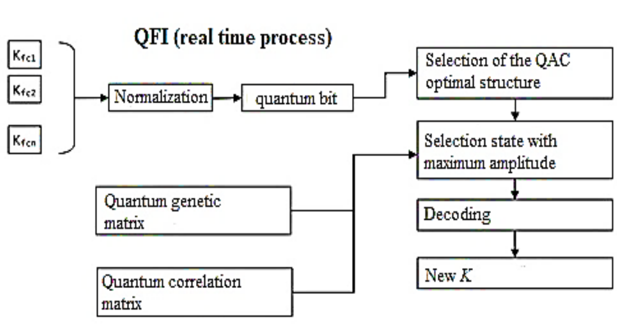

Figure 4. QFI algorithm

Studies conducted in conjunction with ST Microelectronics & Yamaha Motor Co and testing at various CO have confirmed the existence of a synergistic effect of self-organization during the formation of robust KB from designed non-robust imperfect KB using quantum computing. Moreover, an additional information resource for control is based on the extraction of quantum information hidden in classical states embedded in a quantum algorithmic gate. Such ICS design methods allowed achieving global robustness in online, while using the computing resources of the embedded conventional processor of the on-board system.

The use of new quantum computing paradigm and deep machine learning in the group of interaction robots provides the following advantages:

(1) the potential acceleration of computing through the use of quantum evolutionary operators, which will make it possible to fully use the powerful, but slow GA to get the possibility of training the system in online;

(2) the introduction of quantum superposition and quantum-classical correlation operators into the classical algorithm entails the appearance of unique properties of the data processing process, which affects the result of the work of a group of robots;

(3) low dependence on environmental disturbances;

(4) independence from static electricity or movement of the CO or digital video camera;

(5) registration of changes and redistribution of tasks during changes in a group of autonomous agents.

2.3 Control Performance Measure: Thermodynamic Trade-off and Interrelations between Stability, Controllability and Robustness

According to Figure 5, one of the main tasks of designing ICS consists in providing that the developed (chosen) structure possesses the required level of control quality and robustness (supports the required indices of reliability and accuracy of control under the conditions of information uncertainty).

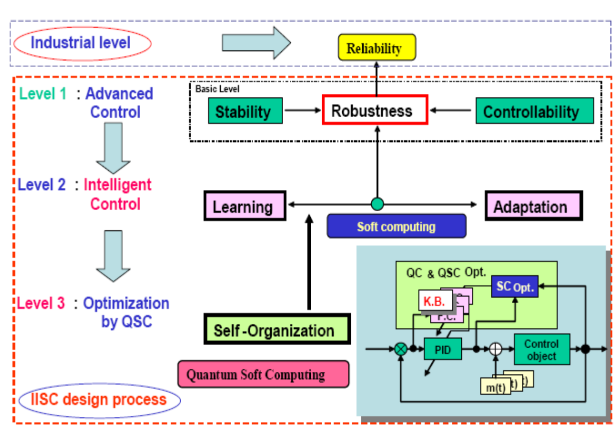

Figure 5. Performance and interrelations between of control quality criteria

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Note that one of the most important and hard-to-solve problems of designing ICS's is the design of robust KB that allow the ICS to operate under the conditions of information uncertainty and risk. The core of technique for designing robust KB of FC's is generated by new types of computing and simulation processes.

Remark. We are witnessing a rapidly growing interest in the field of advanced computational intelligence, a "soft computing" technique. Soft computing integrates fuzzy logic, neural networks, evolutionary computation, and chaos. Soft computing is the most important technology available for designing ICSs and cognitive control. The difficulties of fuzzy logic involve acquiring knowledge from experts and finding knowledge for unknown tasks. This is related to design problems in constructing fuzzy rules. FNN's and GA's are attracting attention for their potential in raising the efficiency of knowledge finding and acquisition. Combining the technologies of fuzzy logic, FNN's and GA's, i.e., soft computing techniques will have a tremendous impact on the fields of intelligent systems and control design.

To explain the apparent success of soft computing, we must determine the basic capabilities of different soft computing frameworks. Recently, the application of ICS structures based on new types of computations (such as soft, quantum computing) has drawn the ever-increasing attention of researchers. Numerous investigations conducted have shown that soft computing possess the following points of favor: soft computing retain the main advantages of conventional automatic control systems (such as stability, controllability, observable ability, etc.); soft computing have an optimal (from the point of view of a given control objective performance) KB; soft computing guarantee the attainability of the required control quality based on the designed KB

One of the main problems of modern control theory is to develop and design automatic control systems that meet the three main requirements: ***stability***, ***controllability***, and ***robustness***. The listed quality criteria ensure the required accuracy of control and reliability of operation of the controlled object under the conditions of incomplete information about the external perturbations and under noise in the measurement and control channels, uncertainty in either the structure or parameters of the control object, or under limited possibility of a formalized description of the control goal. Therefore, in practice of advanced control systems main sources of unpredicted control situations are as following:

(1) *Control object*

① Type of unstable dynamic behavior

(a) Local unstable

(b) Global unstable

(c) Partial unstable on generalized coordinate and non-linear braces

② Time-dependent random structure or parametric excitations

③ Type of model description

(a) Mathematical model

(b) Physical model

(c) Partial mathematical and fuzzy physical model

(2) *External random excitations*

① Different probability density functions

② Time-dependent probability functions

(3) *Measurement system*

① Sensor noise

② Time delay

③ Random time delay with sensor noise

(4) *Different types of reference signals*

(5) *Different types of traditional controllers*

This problem is solved in three stages as following:

(1) the characteristics of stability of the controlled plant are determined for fixed conditions of its operation in the external environment;

(2) a control law is formed that provides the stability of operation of the controlled plant for a given accuracy of control (according to a given criteria of the optimal control);

(3) the sensitivity and robustness of the dynamic behavior of the controlled plant are tested for various classes of random perturbations and noise.

These design stages are considered by modern control theory as relatively independent. The main problem of designing automatic control systems is to determine an optimal interaction between these three quality indices of control performance. For robust structures of automatic control systems, a physical control principle can be proven that allows one to establish in an analytic form the correspondence between the ***required*** level of stability, controllability, and robustness of the control. This allows one to determine the required intelligence level of the automatic control system depending on the complexity of the particular control problem.

Let us briefly consider main physical principles of an energy-based control processes that allow one to establish the interrelation between the qualitative dynamic characteristics of the controlled plant and the actuator of the automatic control system: stability, controllability, and robustness of control. For this purpose, we are employing the informational and thermodynamic approaches that join by a homogeneous condition the criteria of dynamic stability (the Lyapunov's function), controllability, and robustness.

Example: *Thermodynamics trade-off between stability, controllability, and robustness*. Consider a dynamic controlled plant given by the equation

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

where q is the vector of generalized coordinates describing the dynamics of the controlled plant; S is the generalized entropy of dynamic system; u is the control force (the output of the actuator of the automatic control system); $q_d(t)$ is reference signal, $\xi(t)$ is random disturbance and t is the time. The necessary and sufficient conditions of asymptotic stability of dynamic system with $\xi(t)\equiv 0$ are determined by the physical constraints (for example, as for *Port-controlled Hamiltonian Systems* (PCHS) [20]) on the form of the Lyapunov function, which possesses two important properties represented by the following conditions:

(I) This is a strictly positive function of generalized coordinates, i.e., $V>0$;

(II) The complete derivative in time of the Lyapunov's function is a non-positive function,

$$\frac{dV}{dt}\le 0.$$

In general case Lagrangian dynamic system (1) is not lossless with corresponding outputs. By conditions (I) and (II), as the generalized Lyapunov function, we take the function

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

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

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

Assume that the second condition $\frac{dV}{dt}\le 0$ holds. In this case, the complete derivative of the Lyapunov function has the form

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

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

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

Figure 6 shows the role of developed thermodynamic trade-off in robust control design.

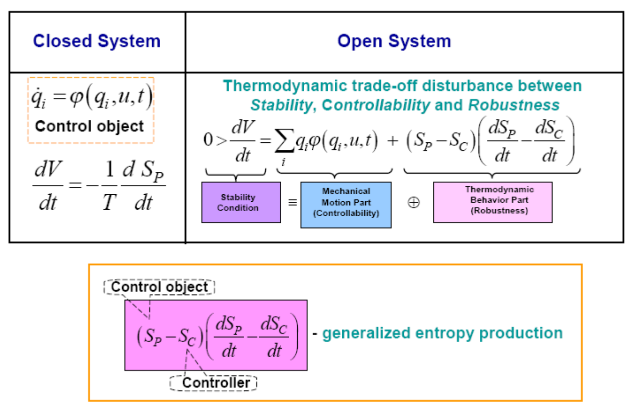

Figure 6. Physical law of intelligent control as background of IFICS design technology

In the case of PCHS [20] we have

$$\underbrace{\frac{dV}{dt}}_{\text{Stability}}=\underbrace{\sum_i x_i\left[\bar{J}_i\left(\bar{x}_i,t\right)-\bar{R}_i\left(\bar{x}_i,S,t\right)\right]\frac{\partial\bar{H}_i\left(\bar{x}_i,t\right)^{\mathrm{T}}}{\partial\bar{x}_i}+\bar{g}_i\left(\bar{x}_i,t\right)\bar{u}_i}_{\text{Controllability}}$$
$$+\underbrace{\left(\Psi-\Upsilon\right)\left(\dot{\Psi}-\dot{\Upsilon}\right)}_{\text{Robustness}}\le 0\tag{4}$$

For the definition of the error system, it is obvious that stabilization (settling the state at the origin) of the error system implies the tracking control of the original system. It was proposed a procedure to realize an error system of a given PCHS by another PCHS via the generalized canoni-

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cal transformation:

$$\bar{x}=\Phi(x,t),\quad \bar{H}=H(x,t)+U(x,t),$$
$$\bar{y}=y+\alpha(x,t),\quad \bar{u}=u+\beta(x,t)\quad ,$$

which preserves the structure of port-controlled Hamiltonian systems with dissipation, that is, the system into an appropriate Hamiltonian system in such a way that the transformed system

$$\dot{\bar{x}}=\left[\bar{J}(\bar{x},t)-\bar{R}(\bar{x},t)\right]\frac{\partial\bar{H}(\bar{x},t)^{\mathrm{T}}}{\partial\bar{x}}+\bar{g}(\bar{x},t)\bar{u},$$
$$\bar{y}=\bar{g}(\bar{x},t)^{\mathrm{T}}\frac{\partial\bar{H}(\bar{x},t)^{\mathrm{T}}}{\partial\bar{x}}$$

satisfies $\bar{x}(t)=0\Leftrightarrow x(t)=x_d(t)$

Relation (4) relates the stability, controllability, and robustness properties.

Remark. This approach was firstly presented in [21]. It was introduced the new physical measure of control quality (3) to complex non-linear controlled objects described as non-linear dissipative models. This physical measure of control quality is based on the physical law of minimum entropy production rate in ICS and in dynamic behavior of complex object. The problem of the minimum entropy production rate is equivalent with the associated problem of the maximum released mechanical work as the optimal solutions of corresponding Hamilton-Jacobi-Bellman equations. It has shown that the variational fixed-end problem of the ***maximum work W*** is equivalent to the variational fixed-end problem of the ***minimum entropy production***. In this case both optimal solutions are equivalent for the dynamic control of complex systems and the principle of minimum of entropy production guarantee the maximal released mechanical work with intelligent operations. This new physical measure of control quality we applied as fitness function of GA in optimal control system design.

In [22] have studied something similar, what was called as “equipartition of energy”. Such state corresponds to the minimum of system entropy. The introduction of physical criteria (the minimum entropy production rate) can guarantee the stability and robustness of control. This method differs from aforesaid design method in that a new *intelligent global feedback* in control system is introduced. The interrelation between the stability of CO (the Lyapunov function) and controllability (the entropy production rate) is used. The basic peculiarity of the given method is the necessity of model investigation for control object and the calculation of entropy production rate through the parameters of the developed model. The integration of joint systems of equations (the equations of mechanical model motion and the equations of entropy production rate) enable to use the result as the fitness function in GA as a new type of CI. Acceleration method of integration for these equations is described in [23].

Main goal of robust intelligent control is support of optimal ***trade-off*** between stability, controllability and robustness with thermodynamic relation as thermodynamically stabilizing compensator. The resetting set is thus defined to be the set of all points in the closed-loop state space that correspond to decreasing controller emulated energy. By resetting the controller states, the CO energy can never increase after the first resetting event. Furthermore, if the closed-loop system total energy is conserved between resetting events, then a decrease in plant energy is accompanied by a corresponding increase in emulated energy.

In concluding this section, we formulate the following conclusions:

(1) The introduced physical law of intelligent control (3) provides a background of design of robust KB’s of ICS’s (with different levels of intelligence) based on soft computing.

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

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

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

Self-organized ICS based on soft computing technology was described in [21] that can support ***thermodynamic trade-off*** in interrelations between ***stability***, ***controllability*** and ***robustness***. As particular case Eq. (3) includes the entropic principle of robustness [24]. The support of optimal thermodynamic trade-off between stability, controllability and robustness in self-organization processes with (3), (4) can be realized using a new quantum control algorithm of self-organization in KB of robust FC based on quantum computing operations (that absent in soft computing toolkit).

3. The Role of Robust Intelligent Control Systems in Advanced Robotics

The process of developing innovative information technologies for the design of embedded self-organizing robust intelligent control systems based on quantum end-to-end artificial intelligence technologies is inextricably linked with the development of scientific and technological progress in areas such as particle physics, robotic systems (sensors, computation processors components), new production technologies, creation of innovative smart materials, analytics of large experimental data, search in unstructured databases. The development of ICS for traditional automated control systems with an increased level of robustness is of significant theoretical, practical and commercial importance. It is imperative that modern control systems maintain the required levels of accuracy and reliability in unforeseen situations. The practice and results of modeling real objects have shown that in conditions of uncertainty or inaccuracy in the initial information, unforeseen situations, or information risk the traditional (using the principle of global negative feedback) and widely used in industry PID-controller often fails to cope with the management task. The application of FC in conjunction with the PID-controller led to the creation of hybrid fuzzy ICSs with different levels of intelligence depending on the completeness and correctness of the designed KB.

The use of soft computing technology (based on GA and FNN) has expanded the field of effective use of FC by adding new functions in the form of learning and adaptation (see Figure 5). However, in the general case of contingency management situations, it is very difficult to design a globally "good" and robust ICS structure. This restriction is especially typical for unforeseen control situations when the CO operates in rapidly changing conditions (sensor failure or noise in the measuring system, the presence of a delay time for control or measurement signals, a sharp change in the structure of the CO or its parameters, etc.). A solution to this kind of problems can be found by introducing the principle of self-organization of KB into the design process of FC, which is implemented and programmatically supported by the developed model of QFI using the methodology of quantum soft computing and Intelligent System of System Engineering [25]. The proposed model of QFI uses private individual KB of FC, each of which is obtained by using SCO for the corresponding operating conditions of the CO and fixed control situations in an external random environment. The design of private individual KB with the application of software tools used for specified control situations is carried out in accordance with the design technology of the ICS and discussed in detail in [26]. The main task solved by QFI is the formation of KB with an increased level of robustness from a finite set of KB for workstations formed using soft computing.

Peculiarities of quantum approach. Recall that the square of the amplitude of the probabilities of a state in quantum mechanics is equal to the classical probability of finding a quantum system in a given state (Bohr's postulate, which has several variants of rigorous justification [27]). From the point of view of the quantum information theory, a pure quantum state is characterized, as is known, by the von Neumann entropy value of zero. Therefore, the intelligent quantum state in the considered case takes place for the minimum informational entropy of the Shannon's quantum state. The desired minimum is achieved, in turn, with the maximum probability P_i of the state. Since P_i, by definition, is the square of the corresponding probability amplitude, the principle of the maximum probability amplitude in the correlated state can be taken as a criterion for selecting the priority "intelligent" correlation (coherent) state in a superposition of possible candidates [28,29]. Thus, by calculating the amplitudes of quantum states in a superposition of states with mixed types of quantum correlation and choosing the maximum among them, a quantum oracle model is implemented that contains the necessary information about the desired solution. Using the standard decoding procedure (the internal product of vectors in a Hilbert space) and selecting the scaling factors for the output values of the projected gain factors, iterative work of algorithm of QFI is carried out. Remote connection of the CO to a stationary computing system opens up the possibility of remote configuration, formation and self-organization of KB in online. The presented model QFI makes it possible to solve the classical problems of designing robust KB in ICS structures that have no analogues among the family of randomized classical algorithms and is characterized by polynomial computational complexity. The design of ICS on QFI is carried out using the developed software toolkit "Quantum Optimizer". The technology of application of quantum fuzzy logic allows combining several KB into a single control system, thereby allowing FNN to work in parallel as quantum neural network.

Remark. From the point of view of computational complexity theories [31-33], the developed algorithm belongs to the class of polynomial algorithms with a limited error - the BPP class (bounded-error probabilistic polynomial

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time), and its quantum generalization - to the BQP class. Accordingly, to quantum algorithm theory and quantum Kolmogorov's algorithmic complexity, this algorithm is effective. This means that structurally the algorithm has polynomial complexity, i.e. the randomized algorithm is polynomial rather than exponential (classic search algorithms) depending on input signals; at the same time, the limited probability of the accuracy of measuring the calculation result is enough to an effective decision making. The following actions are implemented in QFI model [25,34,35]:

(1) the results of the fuzzy inference of each independent FC are processed;

(2) based on the methods of the quantum information theory, valuable quantum information is extracted, hidden in independent (individual) KB;

(3) in online, a generalized robust output control signal is projected on all the sets of KB.

In this case, the output signal of QFI in online is the optimal control signal for changing the coefficient gains of the PID-controller, which includes the necessary (best) quality characteristics of the output control signals of each FC, thereby realizing the principle of ***self-organization***. Therefore, the area of effective functioning of ICS structure can be significantly expanded by including such an important characteristic of control quality as ***robustness***. The robustness of the control signal is the basis for maintaining the reliability and accuracy of control in conditions of uncertainty of information or a poorly formalized description of the operating conditions and / or control objectives [36].

In natural systems the sought robustness property is coded in the algorithm of reproduction of the self-organization process. Therefore, such systems can autonomously handle an unforeseen event using different (close, as regards the idea) approaches: adaptation (learning, evolution) in the framework of which the system corrects its behavior in order to handle the event variation; prediction manifested in the fact that the system can "predict" the change of situation and determine more precisely its behavior (this property is a special case of adaptation and does not require that the system estimates the situation before it occurs); and robustness consisting in the fact that the system can operate and achieve the objective if contingency perturbations of a certain type occur.

The robustness property of the KB is achieved by application of the quantum design algorithm of self-organization in the course of intelligent control which is schematically shown in Figure 7. Figure 7 show the hierarchical levels of the design process using the quantum algorithm, interconnection, and interrelation of the above self-organization properties of robust knowledge bases. The following levels of those shown in Figure7 were considered in detail in [21]: level 3 (physical model and objective of the self-organization control process, and physical interpretation of main operators of the quantum algorithm of KB self-organization control), and level 2 (dynamics of evolution self-organization process).

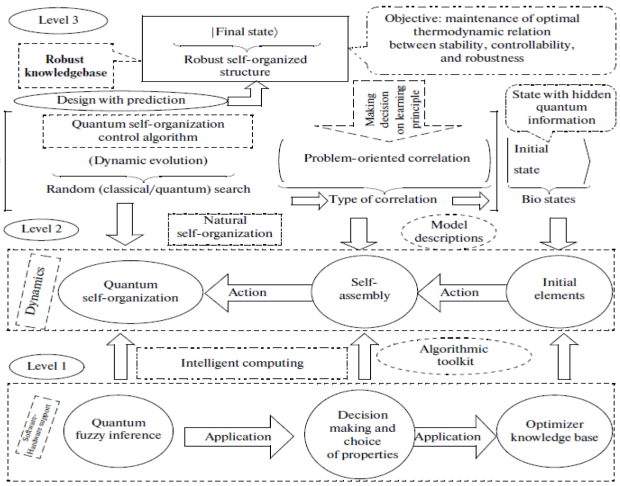

Figure 7. Hierarchical structure of quantum algorithm of design of self-organization of robust KB's in ICS

On Figure 8 is presented the layouts of robots of the "mobile manipulator" type, which were designed by various research groups (HERB: Home Exploring Robotic Butler, STAIR: Stanford Artificial Intelligence Robot and many others), which are a platform for creating new IT and software products.

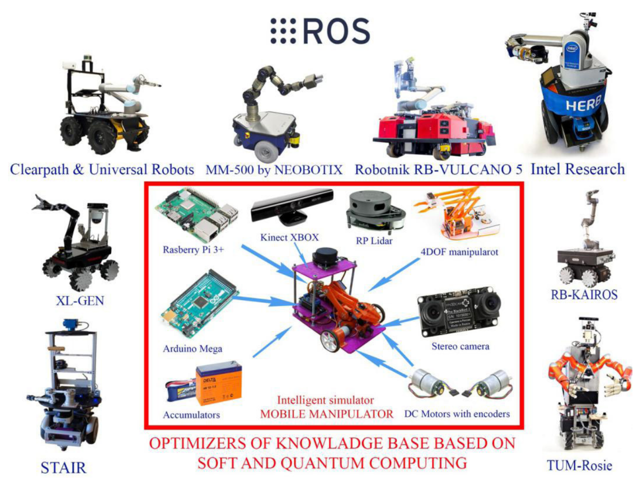

Figure 8. Examples of modern mobile robots with manipulators based on the ROS framework

One of the most striking examples of developing IT projects is the ROS framework. ROS provides libraries and tools to help software developers create robot applications. It provides hardware abstraction, device drivers,

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libraries, visualizers, message-passing, package control, simultaneous localization and mapping (SLAM) navigation, planning and more. The classic task of a mobile manipulator is the task of recognizing an object and manipulating it. In this work, we will consider the mobile intelligent robot shown in Figure 9.

Figure 9. A prototype of a mobile robot with manipulator designed by the laboratory of intelligent control systems (INESYS (EFKO Group), Russia)

Achieving a global goal by a mobile robot for service use with redundant manipulator implies solving the following tasks: pattern recognition in conditions of changing lighting and noises, controlling a multi-link arm and trolley, autonomous navigation in the room using laser rangefinders and stereo vision. The level of robustness of the control laid down in the solution of individual tasks affects the quality of interaction of individual modules and, accordingly, the reliability of the system as a whole. The block diagram of the mobile robot control system is shown in the Figure 10.

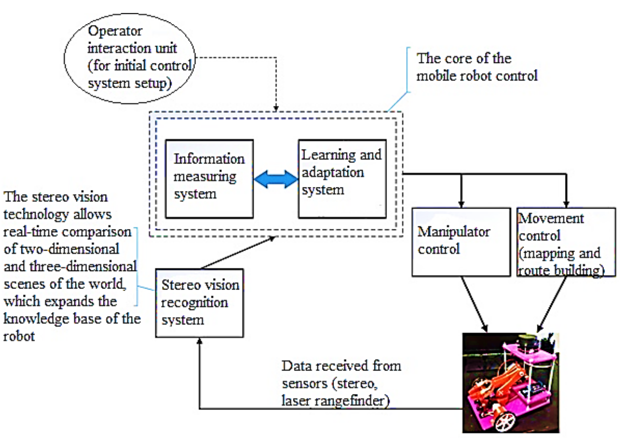

Figure 10. The block diagram of the mobile robot control system

The decomposition of the intelligent control units of the mobile robot control system is shown in the Figure 11.

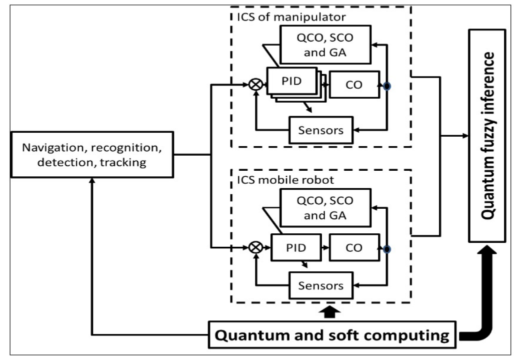

Figure 11. Decomposition of the intelligent control units of the mobile robot control system

Design of an ICS Using the Soft Computing Optimizer

In this section we will consider the process of design and modeling a control system of a redundant manipulator, which was performed in the Matlab/Simulink environment. A fundamental feature in the construction of multi-link manipulators is modularity, which provides adaptability and reconfigurability of the dynamic structure in accordance with the task at hand. For a redundant manipulator the control task can be described as follows:1) ensuring the specified accuracy of the positioning of the functional device of the manipulator;2) determination of the spatial configuration of the manipulator links (invariance is ensured by the redundancy of the number of degrees of freedom), taking into account unforeseen environmental factors. The QFI algorithm [19] includes the step of choosing the type of quantum correlation for constructing the output control signals. We will consider three types of mixed correlations: spatial, spatio-temporal, and temporal [37], and in addition, correlations of various numbers of FC. The dependence of the output signals is determined by the correlation of the sets of input coefficients, where each set is an entangled state. Figure 12 shows the scheme of adding QFI to ICS.

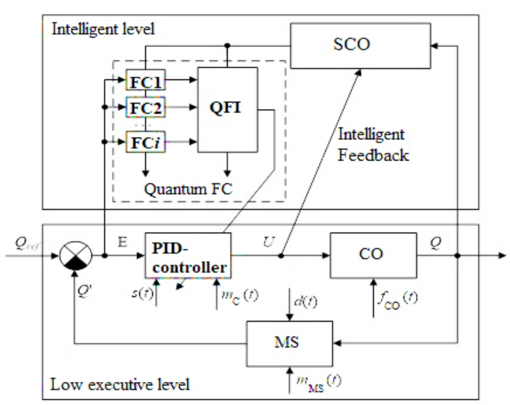

Figure 12. The structure of ICS based on soft and quantum computing

Here Q_{ref} is a reference signal of the navigation and

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pattern recognition system, Q' is a measured variable, E is a control error, $s(t)$ is a control influence limitation, $m_C(t)$,$m_{MS}(t)$ are noises in the control and measurement system channels, U is a control action, $d(t)$ is delay in MS, $f_{CO}(t)$ is external influences on CO, Q is adjustable value. The creation of QFI unit is carried out using the computational intelligence SCO toolkit based on quantum computing [19,38]. In the selected configuration of the ICS structure are implemented seven FC's, each of which independently controls one of the seven links (see Figure 13).

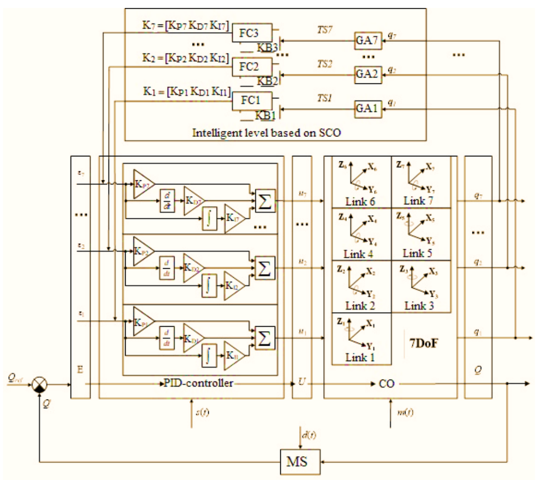

Figure 13. ICS of robot-manipulator with seven degrees of freedom based on SCO

Designations in Figure 13: K_{Pi},K_{Di},K_{Ii}, $i = \overline{1,7}$ are proportional, differential and integral coefficients gain of the PID-controller, where i is the number of the corresponding link of the robot-manipulator, TS_i is training signal, GA_i is genetic algorithm that generates the training signal for the formation of the i-th KB. The standard control situation for the i-th FC is a typical control situation, in the conditions of which the training signal TS_i is received. ICS designed by SCO may contain information about seven control situations (regular or unforeseen) for each of the links.

The process of integrating QFI unit into intelligent level of the control system is shown in Figure 14, where the blocks that are designed using soft and quantum computing technologies are highlighted. Further, ICS with QFI will be called SCO based on quantum computing.

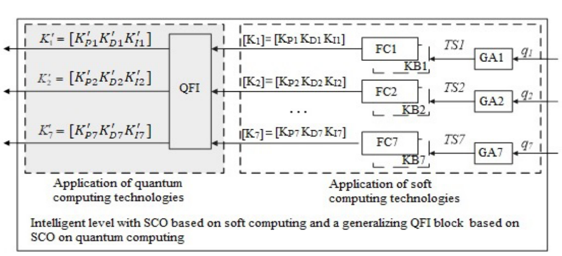

Figure 14. Intelligent level of ICS based on SCO with quantum and soft computing

Testing the robustness of control system models is carried out in experiments in standard and unforeseen control situations. These experiments are described in detail in [37].

We will consider control systems with constant coefficients of the PID regulator and ICS based on SCO on soft computing. A system of quality criteria that takes into account methods for assessing transients of automatic control theory was introduced to evaluate and compare the results of testing control systems. These methods have been adapted for a specific CO (mobile robot-manipulator). The following criteria were highlighted:

(1) solution of the positioning problem in standard control situations PTS_{KCS} (Position Task Solution in known control situations);

(2) solution of the positioning problem in external unforeseen control situations PTS_{ACCS1} (Position Task Solution in the above considered control situations);

(3) solution to the problem of positioning in internal contingency management situations PTS_{ACCS2};

(4) IT performance;

(5) relative overshoot value σ;

(6) relative error in link positioning at the end of a given number of iterations ε;

(7) time of one iteration t;

(8) the complexity of the implementation of control P;

(9) overall assessment of *FCB* management (Full Control Behavior).

Table 1 shows a comparison of ICS based on SCO with quantum computing using spatial correlations with the operation of ICS based on SCO with soft computing.

Table 1. Comparison of ICS based on QCO with ICS based on SCO

	Situation	ICS based on SCO with soft computing	ICS based on SCO with quantum computing	
			Using the correlation of two adjacent FC	Using the correlation of seven FC
1	Regular situations	0,923	1,000	1,000
2	External contingencies	0,744	0,821	0,821
3	Internal contingencies	0,923	0,846	0,923
4	Performance	0,092	0,477	0,459
5	Overshoot	0,969	0,973	0,971
6	Sustainability	0,911	0,962	0,960
7	Single iteration time	0,973	0,961	0,960
8	Implementation complexity	0,946	0,957	0,986
9	General control	0,721	0,816	0,826

Using QFI allowed:

(1) solving the problem of positioning in regular situations;

(2) improving the results of the positioning task in conditions of external unforeseen situations (under internal unforeseen situations the results do not change at best);

(3) increase in the criterion Performance by 5 times;

(4) improving the assessment of general management, the best result is achieved by using spatial correlation of all seven FC's.

Figures 15 and 16 show results of simulation.

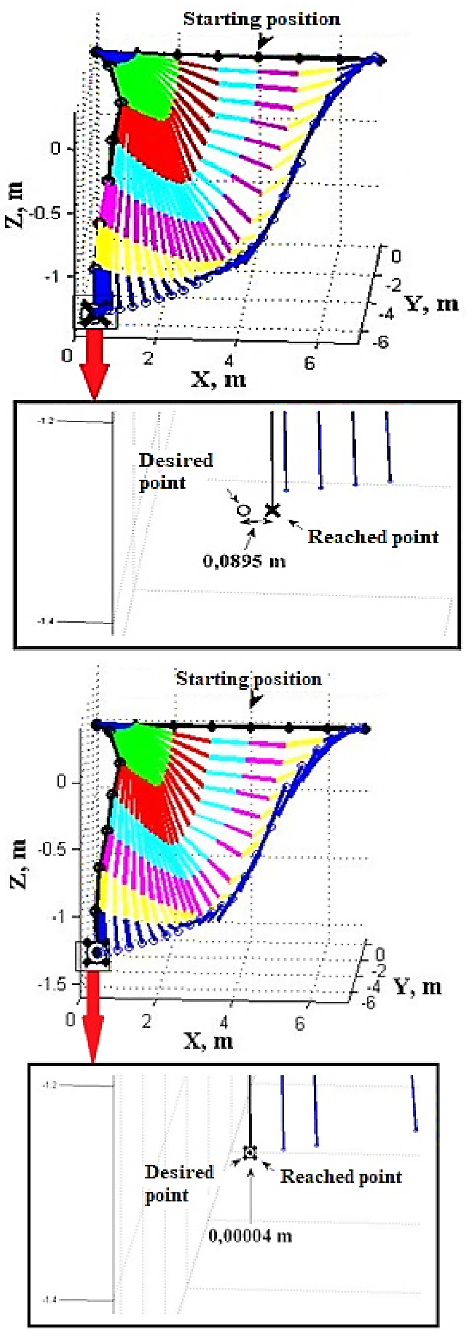

Figure 15. The movement of manipulator in a standard control situation: under control of ICS based on SCO with soft computing (left); ICS based on SCO with quantum computing (right)

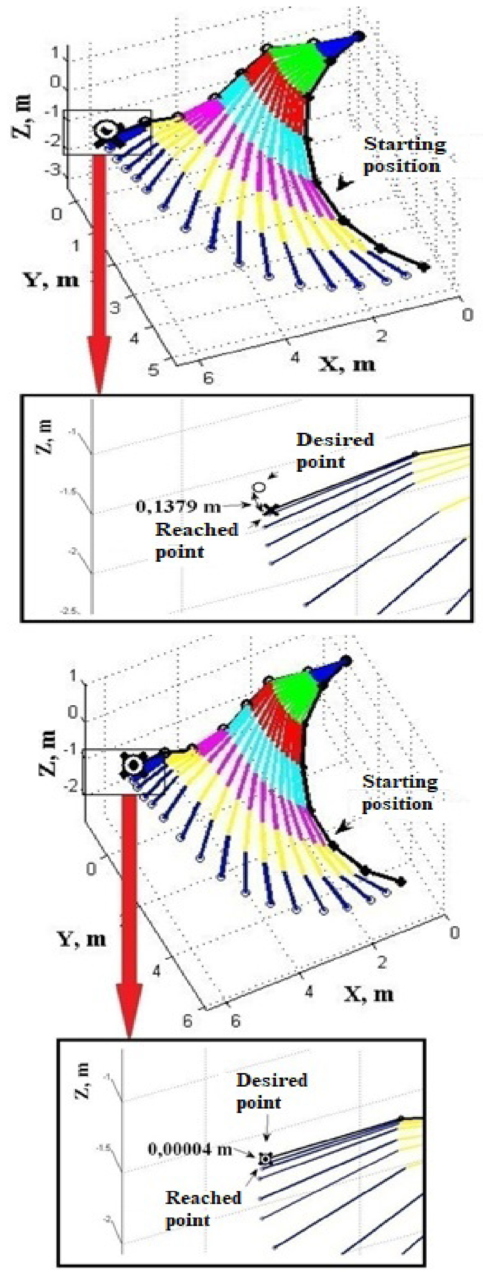

Figure 16. The movement of manipulator in an external unforeseen situation: under control of ICS based on SCO (left); ICS based on QCO (right)

Quantum supremacy. We can conclude that ICS based on QCO (with quantum computing) in the conditions of a regular and external unforeseen control situation solves the problem of precision accuracy positioning a manipulator with 7DoF much better (more 2500 times) than ICS based on SCO (with soft computing). It is also necessary to present the results of an experiment with the positioning of the manipulator under conditions of strong internal disturbing influences [37].

Example. Consider an example of the influence of

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noise in a measurement system (an example of noise in a measurement system is shown in the Figure 17) on the operation of ICS based on soft and quantum computing.

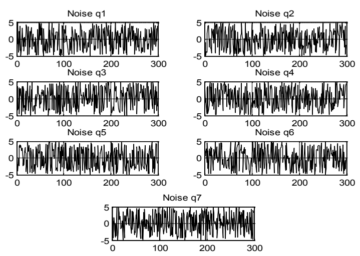

Figure 17. Noise in the measurement system

Figure 18 shows the position of the manipulator during operation ICS based on soft computing (left) and quantum computing (right).

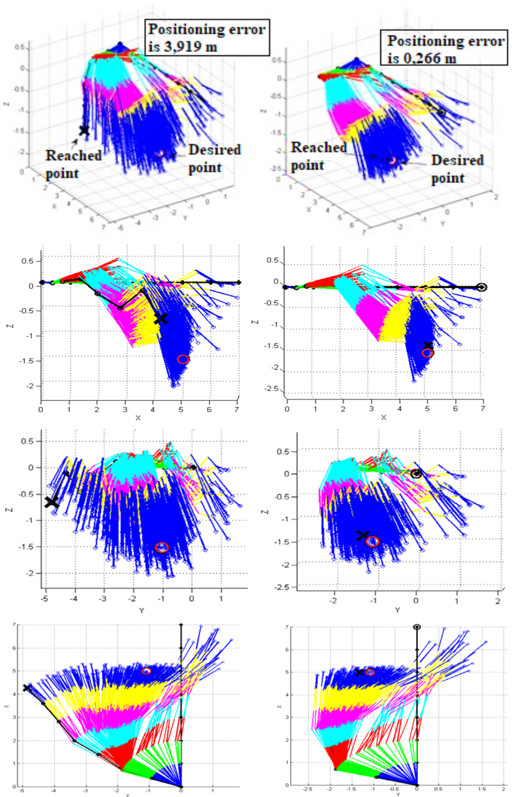

Figure 18. The position of manipulator in space with ICS based on soft computing (left) and quantum computing (right)

In unforeseen situations with the presence of strong noise in the measurement system ICS based on QCO with quantum computing showed an advantage (more 10 times) over ICS based on SCO with soft computing.

One of the key tasks of modern robotics is the development of technologies for the interaction of robotic systems. Modern approaches to solving this problem are based on the theory of multi-agent systems [39] and the theory of swarm artificial intelligence [40]. A multi-agent system is capable of solving complex dynamic tasks for performing collaborative work that does not could be performed by each element of the system individually in a variety of environments without external control, control or coordination. In this case, it's described a net of weakly interconnected robots, working together in order to solve problems that go beyond individual capabilities. Different nodes of such a system, as a rule, have a different level of intellectualization (knowledge, algorithms, computational bases) and various information resources in the design. Each node should be able to modify its behavior depending on the circumstances, as well as plan its communication and cooperation strategies with other nodes. Here indicators of the level of cooperation are: the nature of the distribution of tasks, the combination of various information resources and, of course, the ability to solve a common problem at a given time. The solution of the multi-agent interaction problem can be found by introducing the principle of quantum self-organization (in the process of operation) KB for fuzzy controllers, which is implemented and programmatically supported by the developed model of QFI using quantum and soft computing methodologies and an engineering system - Intelligent System of Systems Engineering (based on the synergistic principle of self-organization of knowledge). Multi-agent system must solve complex dynamic problems of performing the joint work of various devices. Due to the synergistic effect, an additional information resource is created in which the task may not be performed by each element (agent) of the system separately in various environments without external control, control or coordination, but the exchange of knowledge and information allows us to do useful work together to achieve the management goal under the conditions of uncertainty of the initial information and restrictions on the consumption of a useful resource [41]. A physically synergistic effect is the self-organization of knowledge and the creation of additional information that allows a multi-agent system to perform the most useful work with a minimum of loss of useful resource and the required initial information, without destroying the lower executive level of the control system. Together with the informational and thermodynamic laws of intelligent control (the optimal distribution of qualities of "*stability - controllability - robustness*") ICS is designed for multi-agent systems, which guarantees the achievement of the control goal under conditions of uncertainty in the initial information and a limited useful resource.

The lower level of software and hardware implementation represents variations of real-time operating systems and corresponding software in the form of Open source solutions frameworks - add-ons, which taking into account the specific features of the subject area. For example, the Tango Controls add-in (widely used in mega-nuclear projects of nuclear physics), or Robotics Operation System (ROS) with real time Linux. By default, parameters related to the physical features of the implementation of the system itself, control parameters in feedback loops, are used as a custom level in such systems installed by experts or customizable by classical methods. Moreover, the existing tools of intellectualization have a fairly unified standard methodological approach and often do not meet modern requirements for the complexity and required reliability of the developed systems. One of the main problems of the effective use of tools and soft computing technologies (neural networks, evolutionary algorithms, fuzzy logic) in control problems was the solution of the following problems:

(1) an objective definition of the type of MF and its parameters in the production rules in KB;

(2) determination of the optimal structure of FNN in deep machine learning problems (approximation of the training signal with the required (given) error and with a minimum number of production rules in KB);

(3) the use of multicriteria GA in multicriteria control problems in the presence of discrete restrictions on the parameters of the CO.

The listed problems were solved and tested on the basis of SCO software tools using soft computing technology. The developed intelligent tools made it possible to design robust KB based on the solution of one of the algorithmically difficult problems of the theory of artificial intelligence - the extraction, processing and formation of objective knowledge without the use of human expert evaluations.

4. Object Detection and Tracking, Pattern Recognition, Navigation based on Stereo Vision and Computational Intelligence

The combined use of various sensors and their combinations with stereo vision technology allows for a more qualitative and complete construction of the "world scene" of the robot, thereby improving its interaction with the environment. The stereo vision technology, which to some extent repeats the features of the development of natural vision, allows the on-board system to receive information not only about the color and brightness of the object, but also about the distance to it, about its geometric shape, about obstacles to the object, which plays an extremely important role in the tasks of a mobile robot. The intellectualization of the control system, in particular, the use of a neural network approach in the recognition system, significantly reduced the negative impact of external factors on the quality of recognition (recognition error when changing the angle of the object, changing lighting, software sensitivity, etc.).

4.1 Convolutional Neural Network Architecture

As the object of recognition was chosen a plastic cork of an ordinary plastic bottle. With certain image processing, the module also allows tracking the object. In relation to the task of controlling a mobile trolley with a manipulator convolutional neural network (CNN) are often used. The CNN is a multi-layer sensor network, it represents a further development of the multi-layer perceptron, however, unlike the latter, the convolutional network has a much smaller number of weights (the principle of sharing weights). Quite often the CNN model is divided into two main parts: the part responsible for the selection of features, and the part with which classification is performed [42]. Figure 19 shows the structure of the CNN.

Features of the structure of the CNN. The selection of features of an object occurs using layers of convolution and subsampling. Each layer is a set of plates of neurons, which are also called feature maps. The convolution network structure includes two types of layers: convolution layers and subsampling layers. Convolution and subsampling layers are combined into macro layers (a macro layer is a convolution layer followed by a subsampling layer [43]). A set of several architecture-similar macro-layers is called a feature separator in a sensory neural network. Each neuron of the convolution layer and the subsample layer is associated with a receptive field (RF). RF is a certain square area that includes neurons capable of transmitting signals to a neuron that has a given RF. Figure 20 shows a convolutional layer diagram, and also shows the process of its interaction with the previous layer.

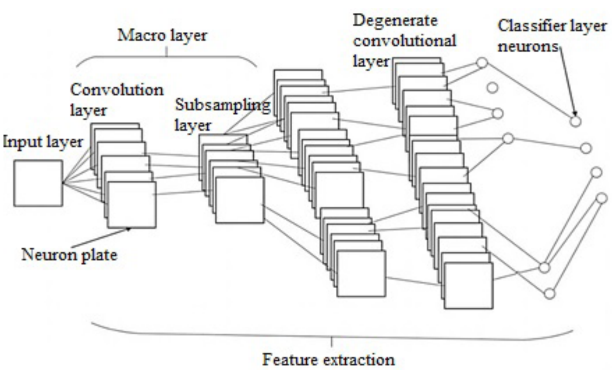

Figure 19. General structure of the convolutional neural network

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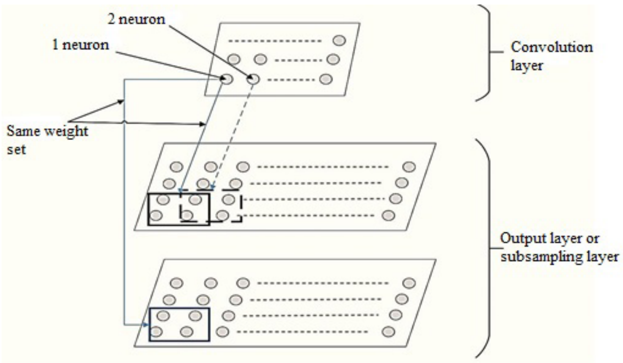

Figure 20. Scheme of interaction of the convolutional layer with the previous layer

Figure 20 makes it clear that RF of each neuron of the convolutional layer is immediately associated with two feature maps of the previous layer (as an example parallel processing of each image channel in RGB color format can be given). A key feature of convolutional layers is that bonds formed within the same feature map have the same set of weights. These are the so-called bound weights. Using the associated weights, certain features are selected in an arbitrary position on the feature map. The connection of the convolutional layer card with several cards of the previous layer provides the opportunity to equally interpret differently presented information [42]. Figure 20 shows that RF of the neurons intersect (the step is subject to adjustment). Reducing the step of applying the RF increases the number of neurons in the map of the next layer. Features of an object with the help of RF and associated weights are extracted [44]. If K_C is the number of neurons that make up the RF of the n-th neuron of the convolutional layer, *Kernel*[k] is the convolution core, b is the displacement of the n-th neuron (b and *Kernel* [k] retain their values for the entire map of the convolutional layer), $x[n + k]$ is the input for the n-th neuron of the convolutional layer (k = 0..K_C-1), then the convolution operation can be displayed by the Eq. (5) [42]:

$$p = b + \sum_{k=0}^{K_c-1} Kernel_k * x_{n+k} \tag{5}$$

The weighted sum p is supplied to the input of the activation function -the response of the neuron is determined [42]. The output of the neuron has the following form:

$$y = f(p) \tag{6}$$

Each neuron of the convolutional layer is a detector of a certain feature that was isolated during training. The interaction of convolution with the activation function of a neuron allows us to assess the degree of presence of a particular trait in the current RF of this neuron. The convolution of an input element with general customizable parameters is an analogue of passing an image on a map through some filter [44].

Figure 21 shows the interaction pattern of the subsampling layer with the previous convolutional layer.

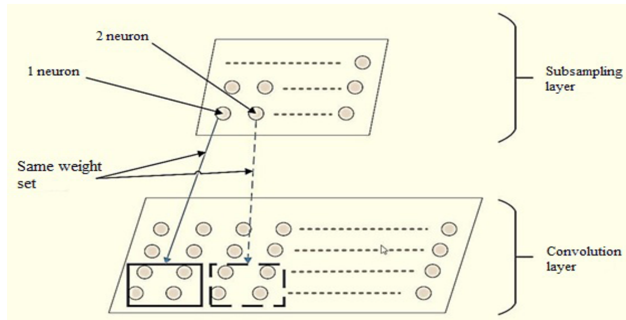

Figure 21. The scheme of interaction of the subsample layer with the previous layer

The main task of the subsampling layer is to reduce the scale of the processed display obtained using the previous convolutional layer. Each map of a subsample layer is associated with only one map of the previous convolutional layer.

It is important to note that RFs of the neurons of the subsample layer do not intersect. Configurable parameters are common to all neurons of each plate. The number of these parameters is equal to two; it does not depend on the number of elements included in the RF of these neurons. Since RFs of the neurons do not intersect, the convolution p for the n-th neuron of the subsample layer is defined as follows:

$$p = b + u * \sum_{k=0}^{K_s-1} * x_{n*K_{s+k}} \tag{7}$$

In Eq. (7) K_S is the total number of neurons included in the RP of the n-th neuron of the subsample layer [43].

The second part of the CNN is a feature classifier. The classifier, as a rule, is a single-layer or two-layer perceptron. The number of neurons in the classifier layer usually corresponds to the number of classes to which the input image belongs. There are no associated weights in the classifier. The weighted sum p for the neuron of the classifier layer can be defined as

$$p = b_n + \sum_{k=1}^{K} x_k * w_{n,k}\,, \tag{8}$$

In Eq. (8) b_n is the offset, different for each neuron, $x[k]$ is the input element, $w[n, k]$ are the custom parameters of the n-th neuron (unique to each neuron), K is the

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input size for the classifier layer [42].

Remark. There are many works [45-50] that are devoted to the creation and training of the CNN. In this work the recognition system based on stereo vision technology uses the classical CNN architecture, which includes convolution and averaging layers. Network training was done with a teacher. In relation to the recognition problem, a teacher is the number of a class that is encoded in a vector. This vector is equal to the size of the output layer of the neural network. This is the desired result corresponding to this input pattern. The actual response is obtained as a result of the reaction of the neural network with the current parameters on the input pattern. Error signal - the difference between the desired signal and the current response of the neural network. It is on the basis of the error signal that the tunable parameters of the neural network are corrected [43]. A significant minus of this training scheme is the great difficulty in creating training samples, however with a few number of classes the negative influence of this factor can be neglected. In the general case a deep machine learning quantum algorithm is used that contains the quantum superposition operator of all input signals with massive data processing parallelism [4].

The error function depends on the system settings being configured. For such a function, one can construct a multidimensional error surface in the coordinates of free parameters. In this case the real surface of the error is averaged over all possible examples, which are presented in the form of input-output pairs. To improve system performance over time, the error value should shift to the minimum. This minimum can be both local and global [43]. The most common and reliable methods for achieving a local or global minimum on the error surface are local optimization methods [51-53].

Remark. Many local optimization algorithms can be divided into two classes: local optimization algorithms with the calculation of partial derivatives of the first order (the method of steepest descent, the method of one-dimensional and two-dimensional optimization of the objective function in the direction of the anti-gradient, the method of conjugate gradients, methods that take into account the direction of the anti-gradient at several steps of the algorithm, etc. .) and local optimization algorithms with the calculation of partial derivatives of the first and second orders (Newton's method, optimization methods with sparse Hessian matrix, quasi-Newton methods, Gauss-Newton method, Levenberg-Marquardt method). In this work, we use the classical error back propagation algorithm with a further generalization to recognition algorithms based on quantum deep machine learning using quantum neural networks and quantum GA [54,55]. Quantum computing is a new computational paradigm that promises applications in several fields, including machine learning. In the last decade, deep learning, and in particular CNN, have become essential for applications in signal processing and image recognition. Quantum deep learning, however remains a challenging problem, as it is difficult to implement non linearities with quantum unitaries. The quantum CNN (QCNN) is a shallow circuit, reproducing completely the classical CNN, by allowing non linearities and pooling operations. The QCNN is particularly interesting for deep networks and could allow new frontiers in image recognition, by using more or larger convolution kernels, larger or deeper inputs (see Appendix 2).

The main and most important stage in the implementation of the recognition system based on the CNN is the stage of formation of the training sample. In a specific case the training sample included 10 classes of objects (cork from a plastic bottle, ball, human face, ballpoint pen, etc.). The total volume of the training sample is 50,000 images (5,000 per class). The volume of the test sample is 10,000 images. A training sample was formed, partly from personally captured images, partly from images downloaded from the Internet. All images are pre-processed (32x32, RGB, resized, mirrored) and divided according to their classification. The design, creation and training of CNN were carried out using the *Keras* library. The structure of the CNN is set using this library directly in the program code, which imposes questions on the choice of the optimal structure.

At the CNN input, the images are received in matrix rather than in vector form (which is necessary to save information about the topology). Input image size 32x32 pixels, format - RGB. The first convolutional layer contains 32 3x3 feature maps (each with its own convolution kernel), i.e. each convolutional neuron is connected to a square 3x3 image. The next convolutional layer has a similar architecture. It is known that convolution layers and subsampling layers are responsible for highlighting certain attributes of various objects (borders, simple colors, and curves) in images. Deepening into the network (going through the following layers of convolution and subsampling) allows you to define less abstract (most characteristic of any class of objects) features. The following dependence can be traced - an increase in the number of macro layers (“Convolution-Subsampling”) makes it possible to find more and more complex features of certain objects in the image. The next step after convolution is averaging (subsampling). This operation reduces the dimension of feature maps obtained from the previous convolution layer. This method is based on the fact that neighboring pixels are very slightly different from each other (the so-called “pixel correlation”). The averaging operation sig-

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nificantly reduces the dependence of the recognition result on the scale of the input image, and also significantly reduces the computational load. A fully connected output layer of 10 neurons contains the probability that the object in the analyzed image belongs to a certain class. Convolutional neural networks are currently one of the best application tools for solving recognition and classification problems. Figure 22 shows that the system correctly recognizes objects even when lighting is degraded.

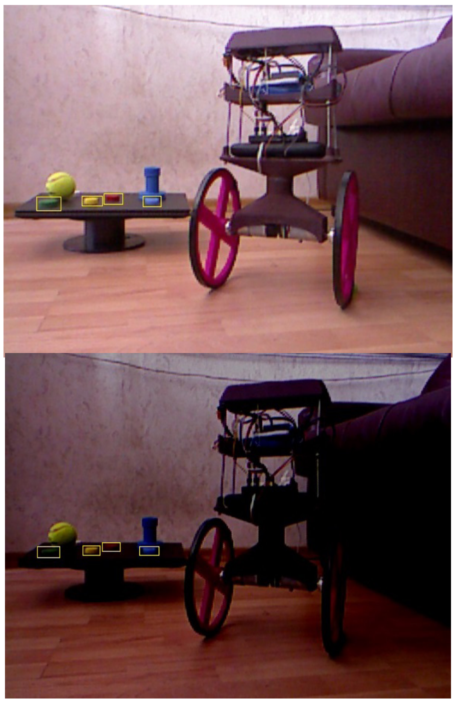

Figure 22. The reaction to the lighting shift

4.2 Navigation Module and Building "World Scene" for a Robot

The navigation module is also an essential part of the mobile robot control system. Using this module, it seems possible to significantly increase the efficiency of the robot.

The development of the navigation system was carried out using the ROS framework. The control system recreates a three-dimensional map (world scene) of the room based on a set of points obtained using a laser rangefinder and a stereo camera. The objects and obstacles present are marked on the resulting map, which allows robot to model its behavior, localize position in space, memorize and build room maps (SLAM) using the Unified Robot Description Format (URDF). Algorithms for calculating the motion path are executed at this moment, which allows the control system to avoid collisions with various objects. As the robot advances in space, the map is dynamically supplemented, control actions on the actuators are recalculated taking into account deviations from the optimal trajectory calculated by the planning package. In this case the movement correction is calculated by PID-controller, while the control parameters (gain factors) are set in accordance with the developed KB. The interaction of the intelligent control modules in the ROS system is provided by the file system level. In this case it is necessary to create a model of a controlled robot and adding this control model to the ROS navigation system. This is necessary to establish spatial relationships between the robot and the objects of the surrounding world. Figure 23 shows a map of the room obtained using the sensor system.

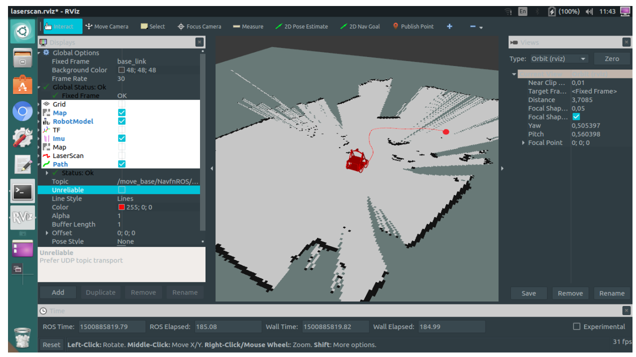

Figure 23. The functioning of the navigation module

The interaction of the main blocks of the mobile robot control system (manipulator control system, motion control system, recognition system) allows us to solve the problem of detecting an object and interacting with it. Figure 24 shows that the recognition system selects and classifies the desired object (bottle cap), and the navigation system paves the route for the found object.

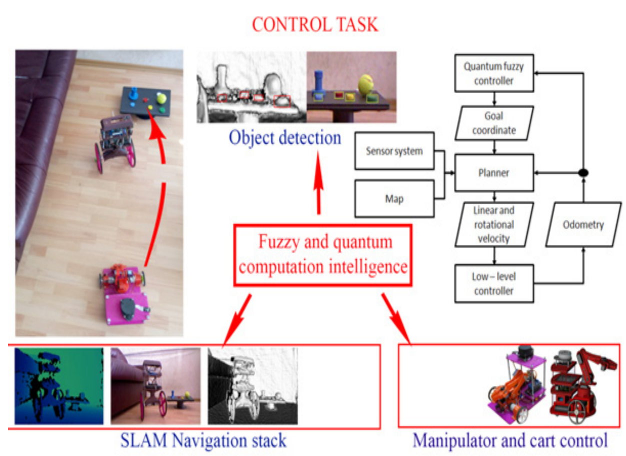

Figure 24. The solution to the task of controlling a mobile robot with manipulator

Figure 24 is presented the description of the task of controlling a mobile robot with manipulator from the point of view of decomposition of control system. Also, the main functional blocks are highlighted, the areas of application of intelligent information technologies are shown.

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4.3 Example

The advantages of using SCO toolkit are clearly demonstrated in an experiment with multi-agent interactions [41]. In this experiment the CO were a robot-manipulator, a robot-bartender and a robot-inverted pendulum.

The visual channel is the main one for receiving information about the surrounding world. Robot receives a lot of information about the environment using a computer vision system. The recognition module is an important part of ICS of a robotic device. The recognition process for the case of interaction of robots is presented in more detail in Figure 25.

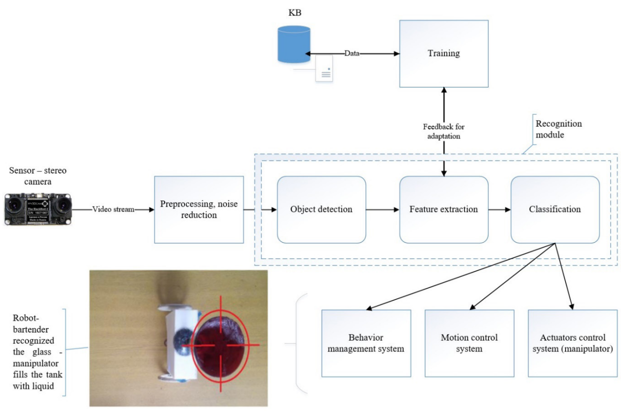

Figure 25. The recognition system in the task of interaction of robots

A glass is installed on the robot-inverted pendulum, which is the object of recognition for the stationary manipulator. The inverted pendulum determines its position relative to the robot-bartender using an infrared camera and "beacons". When the appropriate command is given, robot-inverted pendulum changes its location and moves to the manipulator. When the inverted pendulum is in the visibility range of the stationary manipulator (see Figure 25), recognition system determines the location of the glass and sends a command to the manipulator fill it with liquid (see Figure 26).

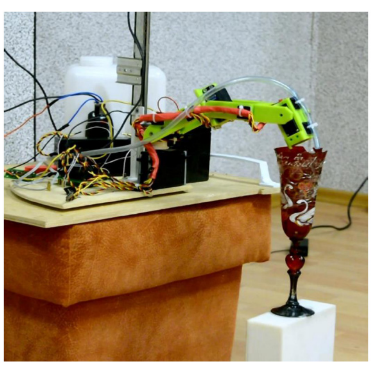

Figure 26. Robot-bartender pours liquid into a glass mounted on a robot-inverted pendulum

As mentioned above, one of the main purposes of the effective and practical use of ICS is the possibility of guaranteed achievement of the control goal with the highest quality control and reducing the consumption of useful system resource. The traditional PID-controller is used in more than 85% of industrial and non-industrial automatic control systems (ACS), including facilities with increased social and economic responsibility. Therefore, one of the important specific (theoretical and practical) problems in the creation of ICS is the development of methods and algorithms to increase the reliability and quality of management of the executive (lower) level of ACS based on the traditional PID-controller. One of the difficulties in developing of ICS for unforeseen control situations is to solve the problem of designing an appropriate KB using objective knowledge about the behavior of CO and fuzzy PID-controllers. The solution of this problem significantly depends on the availability of the development of an algorithmically solvable, physically/mathematically correct model and the practical implementation of the process of extracting, processing and generating objective knowledge without the participation of an expert. The introduction of physical and informational restrictions in the formalized description of CO's model significantly affects the quality of the generated KB. Exclusion of these restrictions from the description of CO's models leads to a loss of robustness of the designed control laws. Therefore, the main goal of developing the basis of information technology for the design of ICS for such a wide class of CO's is the creation of a process for designing robust KB in unforeseen control situations for the executive level, that takes into account real physical and information limitations in the production rules of KB.

The possibility of effective application of robust KB's design technology for ICS (see. Figure 12) in unforeseen control situations is based on the idea of using quantum decision-making strategies in the form of QFI. As a result, the robustness of ICS is formed using QFI in the laws of controlling the gain of the PID-controller. The simulation results (see above - ICS of redundant manipulator) show that the required control quality in unforeseen control situations is not achieved when controlling the FC, while when controlling quantum FC, the control system has the required control quality. It follows that from two non-robust FC's, using quantum self-organization of knowledge, it is possible to design in real time a robust FC, the KB of which satisfies both quality criteria. Therefore, the decomposition of the solution of the problem of multicriteria optimization of robust KB in the unforeseen control situation to particular solutions of optimization subtasks can be physically realized in

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real time in the form of separate reactions of the corresponding individual KB optimized with various fixed criteria of quality and control situation. Aggregation of the obtained particular solutions in the form of a new robust KB is carried out on the basis of QFI. QFI contains the mechanism for the formation of quantum correlation between the obtained particular solutions. As a result, only reactions of a finite number of individual KB's containing extremely achievable control laws in this unforeseen situation are used. The control laws of fuzzy PID-controller formed by the new robust KB have a simpler physical implementation and as a result contain the best characteristics of individual control quality criteria for an unforeseen control situation. It is also necessary to mention that according to the *Thermodynamics trade-off between stability, controllability, and robustness* (see paragraph 2.3), the property of robustness (by its physical nature) is an integral part of the property of self-organization. The required level of robustness of ICS is achieved by fulfilling the principle of minimum production of generalized entropy. The principle of minimum entropy production in the control system is the physical principle of optimal functioning with a minimum of useful work. This principle underlies the development of a robust control system (which is very important for such complex systems as, for example, a team of robots). The approach based on QFI (described in this paper) guarantees the necessary condition for self-organization - the minimum of the required initial information in the training 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.

The experiment with multi-agent interaction, in which the robot manipulator participated (ICS of this robot is described in this chapter), allows us to draw the following conclusion - the use of SCO based on quantum computing can significantly increase the robustness of the control system. The toolkit allows to configure complex control systems with many of control loops; the number of input variables and the size of the resulting KB are limited only by the hardware characteristics of the computer and CO. The developed interaction options show the possibilities of using these systems in a wide range of tasks, such as automation of warehouses and production facilities, automatic catering establishments, emergency response, etc. The main feature of a multi-agent system is the synergistic effect arising from the combination of several robotic systems, when the result of the functional interaction far exceeds the capabilities of each of the robots separately.

5. Conclusion

Intensification of the production process, increasing complexity and the number of various technical products, increasing the processing power of processors indicate the necessity for development of design technologies and the introduction of intelligent systems in the control loop. In turn, it is necessary to have intelligent tools to configure similar systems in various subject areas. An increasing in the computational basis (types of calculations) of a software product leads to an increase in the quality and reliability of control, adding the properties of adaptation and learning to the feedback loop. However, increasing the reliability of the control system leads to an increase in tunable parameters and, as a result, to increasing the complexity of tuning such systems. A control system can cope with an unpredictable environment autonomously using different but closely related approaches:

(1) Adaptation (learning, evolution) - the system changes its behavior to cope with the change.

(2) 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.

(3) Robustness - the system is robust if it continues to function in the face of perturbations. This can be achieved with modularity, degeneracy, distributed robustness, or redundancy.

(4) Modularity: firstly, the approach to incorporating elements of intelligent computing into classical control systems implies non-destruction of the lower executive level (which ensures minimal interposal in the CO hardware). Secondly, when working with complex control objects, it is necessary: ① to separate the control blocks to reduce complexity, ② to organize coordination control of the separated blocks to improve the quality of control, which QFI does well described on the example of the ICS based on SCO on quantum computing of 7DoF manipulator in this article.

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. The main components and their interrelations in the information design technology are based on new types of (soft and quantum) computing. The key point of this information design technology is the use of the method of eliciting objective knowledge about the control process irrespective of the subjective experience of experts and the design of objective KB's of a FC, which is principal component of a robust ICS. The developed SCO toolkit implements mechanisms for creating, configuring, and transmitting control parameters in the form of control signals received from KB of FC without destroying the low executive level. The use of soft computing and developed ICS design technologies reduces the impact of expert judgment in the training and configuration of ICS.

From computer science viewpoint, QA of QFI model plays the role of the information algorithmic and SW-platform support for design of self-organization process. Quantum computing, which ensures robustness of ICS, introduces the property of self-organization, allows CO to function effectively in conditions of a lack of a priori information. The use of this kind of computing can reduce the influence of the hardware (for example, reducing the number of sensors) on the effectiveness of the control system. Technologies for remote configuration and transmission of KB allow the CO to receive KB from the SCO unit or from other CO, which makes it possible to manage structurally new objects, such as teams of robots, multi-agent systems, complex automated production, etc. In addition, this technology gives CO ability to update and adapt KB for a specific control situation, including contingency.

The experiments described above demonstrate that the inclusion of QFI module in ICS based on SCO with soft computing made it possible to provide a complete solution to the positioning problem in standard control situations and in the conditions of external unforeseen control situations. The QFI module significantly improved the accuracy index of the positioning of the functional device under strong internal disturbances, the performance index improved 5 times, and the relative error in the positioning of the links decreased. It is important to note that we must to organize the separation of control during the design of ICS for complex CO's (precisely such CO's appear in the experiments described above). This is necessary for the organization of coordination management without significantly increasing the complexity of the control system. However, such a management decomposition often leads to a mismatch of work and a decrease in the quality of management. In the example of multi-agent interaction QFI module, using data from stereo vision module, successfully generates a generalized robust control signal. Moreover, control robustness is achieved even with a limited set of sensors and in the presence of internal and external disturbing influences.

Appendix 1: *Emotional Learning and Its utilization in Control Engineering* [56]. The Limbic System, as part of the mammalian creatures' brain, is mainly in charge of the emotional processes. 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. In this section, we try to describe briefly these main components and their tasks. Figure A1.1 illustrates the anatomy of the main components of Limbic System. The first sign of affective conditioning of the system appears in Amygdala which is a small almond-shaped in sub-cortical area. This component is placed in a way to communicate with all other Sensory Cortices and areas within the Limbic System. The Amygdala connections to/from other components are illustrated in Figure A1.2. 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.

In a reciprocal connection, the Orbitofrontal Cortex, as of another component of the brain system, interacts with the Amygdala. The main interrelated function of this component is: Working Memory, Preparatory Set and Inhibitory Control. The current and recent past events are represented in the Working Memory. The Preparatory Set is the priming of other structures in anticipation of impending action. Inhibitory Control is the selective suppression of areas that may be inappropriate in the current situation. More specifically, the Orbitofrontal Cortex takes action in omission of the expected reward or punishment and control the extinction of the learning in the Amygdala. Another component in this area is Thalamus which lies next to the basal ganglia. It is a non-homogeneous sub-cortical structure and a way-station between cortical structures and sub-cortical. Moreover, various parts of the Thalamus also relay the majority of sensory information from the peripheral sensory systems to the Sensory Cortices. Particularly, the Thalamic Sensory Inputs going to the Amygdala are believed to mediate inherently emotionally charged stimuli as well as coarsely resolved stimuli in general. The Thalamus signal going to the Amygdala evades the processes involved in the Sensory Cortex and other components of the system. Therefore, Amygdala receives a non-optimal but fast stimulus from the Thalamus which among the input stimuli is often known as a characteristic signal.

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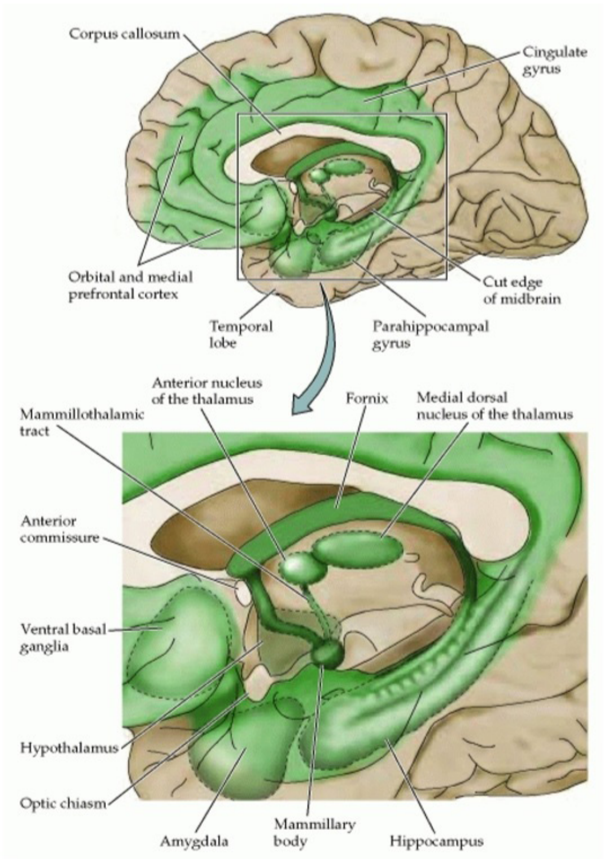


Figure A1.1. The major brain structures associated with the Limbic System

The next component is the Sensory Cortex close to the Thalamus which receives its input from the latter one. In fact, Sensory Cortex processes the information from the sensory areas. The Sensory Cortex sends highly analyzed input to the Amygdala and Orbitofrontal. Generally, the mammalians use these areas of their Limbic System for higher perceptual processing. Below the Thalamus, lies another component named Hypothalamus which is apparently in charge of regulation of the endocrine system, the autonomous nervous system and primary behavioral surviving states. The lateral region of Hypothalamus is connected to various regions of the Amygdala and vice versa. The connections are believed to have a major role in motivational control of the Structures within the Hypothalamus. 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.

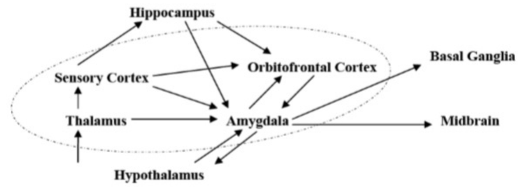


Figure A1.2. Connections of the Amygdala with other components of the Limbic System

The main issue in using the emotional learning for different applications is defining the sensory and emotional signals in such a way that properly represent the state and objectives of the system. Some of researchers have developed intelligent systems based on BELBIC which in this section some of the designed applications are briefly introduced and the results of simulation are demonstrated in some applications. Rouhani and co-workers used BELBIC in a neuro-fuzzy model of microheat exchanger. First, a locally linear learning algorithm called Locally Linear Mode Tree (LoLiMoT) was applied to build the neuro-fuzzy model. Then, the BELBIC based on PID control was adopted for the micro-heat exchanger plant. The performance of presented controller was compared with classic PID controller. Figure A1.3 and Figure A1.4 show the closed-loop system response using BELBIC and PID controller respectively. As shown the performance of the system using BELBIC is much better than that of PID controller.

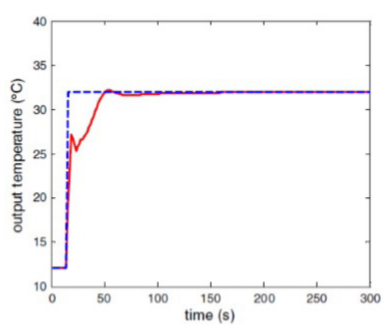


Figure A1.3. Closed-loop system response using BELBIC with LoLiMoT identifier

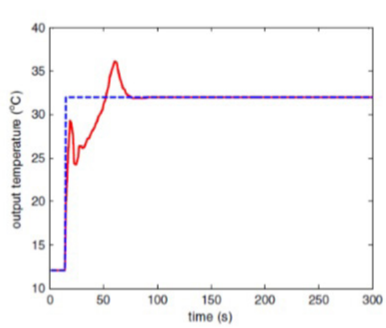


Figure A1.4. Closed-loop system response using PID with LoLiMoT identifier

Jafarzadeh et al. proposed an intelligent autopilot for a 2-DoF helicopter model based on BELBIC. The majority of previous systems were based on the linearization model or through several linearization techniques for helicopter that made the proposed controls unreliable. The designed model used a BELBIC controller and feedback linearization technique to a nonlinear model of a helicopter. In this method, the states of the system have been separated into two parts, and each part has been controlled by one of the control inputs. The performance of the two mentioned controllers simulated the in Simulink. The simulation results of controller system by BELBIC controller and feedback linearization controller have been demonstrated in the Figure A1.5, and in Figure A1.6, the control inputs of the system have been shown.

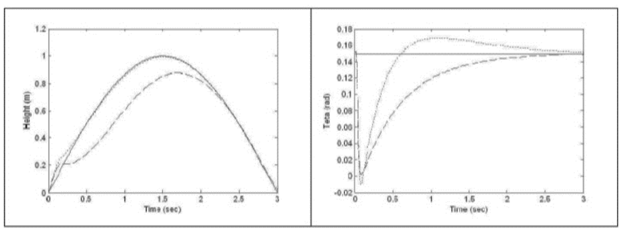


Figure A1.5. Height (left) and Collective rotor blade angle (right) of helicopter (Solid: set point, Dashed: feedback linearization, Dotted: BELBIC)

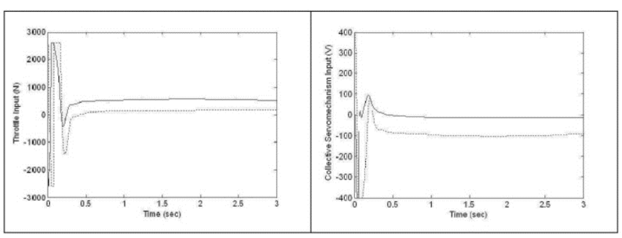
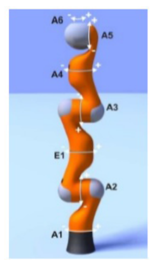


Figure A1.6. First (left) and second (right) control input of helicopter (Solid: feedback linearization, Dotted: BELBIC)

It can be seen from these simulations that the tracking performance of BELBIC controller for the height is better than Feedback linearization controller, but in the sense of steady state the performance of both controllers is satisfactory. However, stability guarantee is an important drawback for this controller.

An intelligent control based on BELBIC has been introduced for speed and flux control of an induction motor. It was a novel and simple model of induction motor drives control which controlled motor speed and flux accurately, without needing to use any conventional controllers and independent of motor parameters. In order to evaluate this emotional controller, digital computer simulations have been performed using Matlab/Simulink. The results showed that the emotional controller had some gains, which gave good freedom for choosing desired responses in terms of overshot, settling time, steady state error and smoothness. These made the controller effective and flexible in high performance applications. Moreover, Simple structure, fast auto learning and high tracking potency of BELBIC have been made to present a new control plant that is independent of motor parameters and controls speed and flux simultaneously.

As a demonstration of the performance of the BELBIC controller in real-world applications beyond numerical simulation, it will be implemented on a KUKA Lightweight Robot (LWR), a 7DoF KUKA LWR4+ [57]. Bio-inspired by the human arm and with a payload of 7 kg and its 7 axes, all equipped with internal position as well as force-/torque-sensors, this redundant robot offers a range of features which are essential for the considered application. The seven revolute joints of the industrial robot are driven by brushless motors via harmonic drives. The working envelope is described in Figure A1.7.



Axis data	Motion range	Speed with rated payload	Maximum torque
Axis A1 (J1)	± 170°	110°/s	176 Nm
Axis A2 (J2)	± 120°	110°/s	176 Nm
Axis E1 (J3)	± 170°	128°/s	100 Nm
Axis A3 (J4)	± 120°	128°/s	100 Nm
Axis A4 (J5)	± 170°	204°/s	100 Nm
Axis A5 (J6)	± 120°	184°/s	38 Nm
Axis A6 (J7)	± 170°	184°/s	38 Nm

Figure A1.7. Axes-nomination of the KUKA LWR4+ (KUKA, 2012) (left); Description of the work envelope of the KUKA LWR4+ (right)

The scientific work [57] is dedicated to the tasks of namely path following and position control. The tracking of complex freeform-trajectories by robotic manipulators is essential to many manufacturing processes like grinding, welding, polishing or gluing. Besides pick-and-place operations, path following is the most common type of automation tasks. With conventional controllers satisfactory performance is obtained for basic constrained motions and therefore they are still widely used in industry. The use of these conventional control schemes is however restricted to robotic manipulators with well-known dynamic and kinematic parameters following rather simple continuous paths in a disturbance-free environment. The desire to extend position control to robotic manipulators with unknown parameters following discontinuous freeform paths in the presence of disturbances explains the interest in the trajectory tracking control problem.

As a verification of the performance of the suggested control scheme, the controller is evaluated through simulation in a Matlab/Simulink-environment. For the simulation a two-link planar robotic manipulator with revolute joints. Excellent simulation-results were obtained. Robot-external

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disturbances are added as time-dependent 2-dimensional function. Internal uncertainties are added in the form of maximal +/-10% deviations from the dynamic parameters-values. Switching constraints are implemented in the form of a desired trajectory switching between different curved and straight segments as shown in Figure A1.8. The desired continuous trajectory is not differentiable.

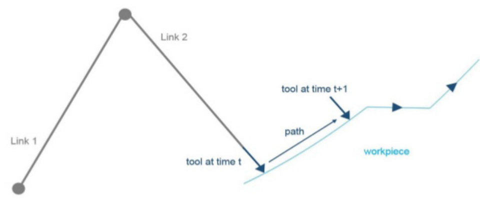

Figure A1.8. Trajectory to be tracked by the tool on the workpiece surface in the simulated application; the arrows indicate the movement-direction

Table A1.1 shows the performance of the three considered controllers for trajectory tracking of discontinuous freeform paths, exhibited on the example shown in Figure A1.8.

Table A1.1. Absolute maximal, minimal and mean position errors for both manipulator-links using PID-, Computed Joint Torque (CJT)-control and BELBIC-SMC

	PID		CJT		BELBIC- SMC	
	$q_{error,1}$	$q_{error,2}$	$q_{error,1}$	$q_{error,2}$	$q_{error,1}$	$q_{error,2}$
Max [rad]	0.5685	0.3877	0.3945	0.2477	0.0115	0.0122
Min [rad]	0.0046	0.0020	0.0046	0.0045	1.3567e-04	9.5147e-06
Mean [rad]	0.4938	0.2722	0.3513	0.1714	0.0053	0.0033

In order to demonstrate the efficiency of the suggested controller in real-world applications beyond numerical simulation, an experimental validation is performed. The first experiment is a goal-reaching task. The task is about moving the robot's joints consecutively to a specified goal position. Table A1.2 shows that the BELBIC-SMC-concept outperforms PID- and Computed Joint Torque-control.

Table A1.2. Absolute maximal, minimal and mean position errors for all manipulator-links using PID-, Computed Joint Torque (CJT)-control and BELBIC-SMC when reaching a desired goal position

PID		$q_{error,1}$	$q_{error,2}$	$q_{error,3}$	$q_{error,4}$	$q_{error,5}$	$q_{error,6}$	$q_{error,7}$
	Max [rad]	0.0409	0.0259	0.0205	0.0096	0.0010	0.0002	0.0002
	Min [rad]	0.0044	0.0070	0.0094	0.0095	0.0010	0.0002	0.0002
	Mean [rad]	0.0163	0.0206	0.0196	0.0096	0.0010	0.0002	0.0002
CJT		$q_{error,1}$	$q_{error,2}$	$q_{error,3}$	$q_{error,4}$	$q_{error,5}$	$q_{error,6}$	$q_{error,7}$
	Max [rad]	0.0409	0.0258	0.0250	0.0096	0.0019	0.0005	2.33451e-05
	Min [rad]	0.0003	0.0003	0.0087	0.0044	0.0010	0.0001	1.65384e-05
	Mean [rad]	0.0162	0.0182	0.0217	0.0075	0.0016	0.0003	2.19066e-05
Belbic -SMC		$q_{error,1}$	$q_{error,2}$	$q_{error,3}$	$q_{error,4}$	$q_{error,5}$	$q_{error,6}$	$q_{error,7}$
	Max [rad]	0.0409	0.0259	0.0205	0.0096	0.0010	0.0002	0.0001
	Min [rad]	0.0001	1.07288e-06	4.48376e-05	3.09944e-06	0.0010	0.0002	8.71101e-05
	Mean [rad]	0.0273	0.0212	0.0182	0.0092	0.0010	0.0002	9.35719e-05

The simulation verifies the tracking performance of the BELBIC-SMC-controller for the chosen case. The BELBIC-SMC-controller outperforms both, the PID- and the Computed Joint Torque-controller. The freedom-shape and especially the discontinuity of the path deteriorate the tracking performance of the conventional controllers.

Appendix 2: *quantum computing in deep convolutional neural networks* [58]. The growing importance of deep learning in industry and in our society will require extreme computational power as the dataset sizes and the complexity of these algorithms are expected to increase. Quantum computers are a good candidate to answer this challenge. The recent progress in the physical realization of quantum processors and the advances in quantum algorithms increase more than ever the need to understand their capabilities and limits. In particular, the field of quantum machine learning has witnessed many innovative algorithms that offer speedups over their classical counterparts. Quantum deep learning, the problem of creating quantum circuit that enhance the operations of neural networks, has been studied in several works. It however remains a challenging problem as it is difficult to implement non linearities with quantum unitaries. CNN are a type of deep learning architecture well suited for visual recognition, signal processing and time series. In this work we propose a quantum algorithm to perform a complete convolutional neural network (QCNN) that offers potential speedups over classical CNNs.

The adaptation of the CNNs to the quantum setting implies some modifications that could alter the efficiency of the learning or classifying phases. In work [58] were presented some experiments to show that such modified CNNs can converge correctly, as the original ones. The experiment, using the PyTorch library, consists of training classically a small convolutional neural network for which was added a "quantum" sampling after each convolution. In the following results, we can see that r quantum CNN is able to learn and classify visual data from the widely used MNIST dataset. This dataset is made of 60.000 training images and 10.000 testing images of handwritten digits. Each image is a 28x28 grayscale pixels between 0 and 255 (8 bits encoding), before normalization.

Let's first observe the "quantum" effects on an image of the dataset. In particular, the effect of the capped non linearity, the introduction of noise and the quantum sampling (see Figure A2.1).

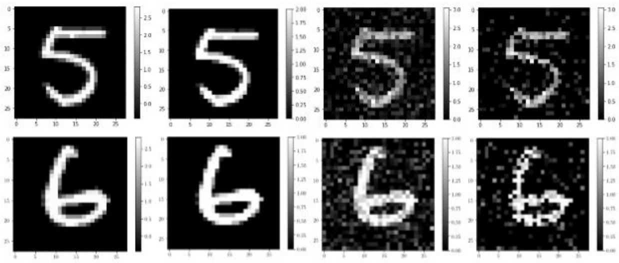

Figure A2.1. Effects of the QCNN on a 28x28 input image

Note: From left to right: original image, image after applying a capReLu activation function with a cap C at 2.0, introduction of a strong noise during amplitude estimation with = 0.5, quantum sampling with ratio σ = 0.4 that samples the highest values in priority. The useful information tends to be conserved in this example. The side gray scale indicates the value of each pixel. Note that during the QCNN layer, a convolution is supposed to happen before the last image but we chose not to perform it for better visualization.

I. Kerenidis et al. present the full simulation of our quantum CNN. In the following, they use a simple network made of 2 convolution layers, and compare quantum CNN to the classical one. The first and second layers are respectively made of 5 and 10 kernels, both of size 7x7. A three-layer fully connected network is applied at the end and a softmax activation function is applied on the last layer to detect the predicted outcome over 10 classes (the ten possible digits). Note that researchers didn't introduce pooling, being equivalent between quantum and classical algorithms and not improving the results on our CNN. The objective of the learning phase is to minimize the loss function, defined by the negative log likelihood of the classification on the training set. The optimizer used was a built-in Stochastic Gradient Descent. Using PyTorch, researchers have been able to implement the following quantum effects (the first three points are shown in Figure A2.1):

(1) The addition of a noise, to simulate the approximation of amplitude estimation during the forward quantum convolution layer, by adding gaussian noise.

(2) A modification of the non-linearity: a ReLu function that becomes constant above the value T (the cap).

(3) A sampling procedure to apply on a tensor with a probability distribution proportional to the tensor itself, reproducing the quantum sampling with ratio σ.

(4) The addition of a noise during the gradient descent, to simulate the quantum backpropagation, by adding a gaussian noise centered on 0 with standard deviation δ, multiplied by the norm of the gradient.

In the following researchers report the classification results of the QCNN when applied on the test set (10.000 images). They distinguish to use cases: in Table 4 the QCNN has been trained quantumly as described in this paper, whereas in Table 5 they first have trained the classical CNN, then transferred the weights to the QCNN only for the classification. This second use case has a global running time worst than the first one, but we see it as another concrete application: quantum machine learning could be used only for faster classification from a classically generated model, which could be the case for high rate classification task (e.g. for autonomous systems, classification over many simultaneous inputs). Are presented the test loss and accuracy for different values of the sampling ratio σ, the amplitude estimation error ϵ, and for the backpropagation noise δ in the first case. The cap C is fixed at 10. These values must be compared to the classical CNN classification metrics, for which the loss is 0.129 and the accuracy is 96.1%. Note that researchers used a relatively small CNN and hence the accuracy is just over 96%, lower than the best possible accuracy with larger CNN.

Table A2.1. QCNN trained with quantum backpropagation on MNIST dataset. With C = 10 **fi**xed

QCNN Test - Classification					
σ	ϵ	0.01		0.1	
	δ	0.01	0.1	0.01	0.1
0.1	Loss	0.519	0.773	2.30	2.30
	Accuracy	82.8%	74.8%	11.5%	11.7%
0.2	Loss	0.334	0.348	0.439	1.367
	Accuracy	89.5%	89.0%	86.2%	54.1%
0.3	Loss	0.213	0.314	0.381	0.762
	Accuracy	93.4%	90.3%	87.9%	76.8%
0.4	Loss	0.177	0.215	0.263	1.798
	Accuracy	94.7%	93.3%	91.8%	34.9%
0.5	Loss	0.142	0.211	0.337	1.457
	Accuracy	95.4%	93.5%	89.2%	52.8%

Table A2.2. QCNN created from a classical CNN trained on MNIST dataset. With δ = 0.01 and C = 10 **fi**xed

QCNN Test - Classification			
σ	ϵ	0.01	0.1
0.1	Loss	1.07	1.33
	Accuracy	86.1%	78.6%
0.2	Loss	0.552	0.840
	Accuracy	92.8%	86.5%
0.3	Loss	0.391	0.706
	Accuracy	94,3%	85.8%
0.4	Loss	0.327	0.670
	Accuracy	94.4%	84.0%
0.5	Loss	0.163	0.292
	Accuracy	95.9%	93.5%

QCNN is able to learn despite the introduction of noise,

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tensor sampling and other modifications. In particular it shows that only a fraction of the information is meaningful for the neural network, and that the quantum algorithm captures this information in priority. This learning can be more or less efficient depending on the choice of the key parameters. For reasonable values of these parameters, the QCNN is able to converge during the training phase. It can then classify correctly on both training and testing set, indicating that it does not overfit the data. The learning curves sometimes present a late start before the convergence initializes, in particular for small sampling ratio. This late start can be due to the random initialization of the kernel weights, that performs a meaningless convolution, a case where the quantum sampling of the output is of no interest. However it is very interesting to see that despite this late start, the kernel can start converging once they have found a good combination. Overall, it is possible that the QCNN presents some behaviors that do not have a classical equivalent. Understanding their potential effects, positive or negative, is an open question, all the more so as the effects of the classical CNN's hyperparameters are already a topic an active research.

In work [59] demonstrates the potential of Quantum-Classical Convolutional Neural Networks (QCCNN) by applying it to the Tetris dataset. Researchers create a Tetris image dataset that consists of 1000 grey-scale images with shape 3×3, in which each grey-scale image is a simulated Tetris brick.

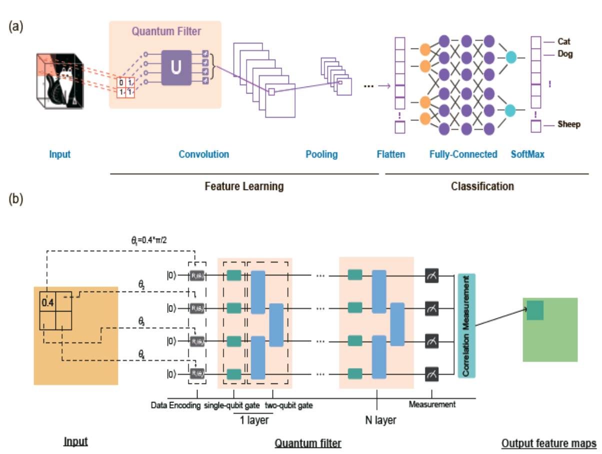

Figure A2.2. (a) Hybrid quantum-classical Convolutional Neural Network (QCCNN); (b) Details of of parametric quantum circuit design, which is made of interlaced single-qubit layer and two-qubit layers

Remark. On Figure A2.2 the input demonstrated here is a two-dimensional array, which is sent to a quantum convolutional layer of 6 filters. Each filter takes a 2x2 window, translating it into a separable 4-qubit quantum state, and evolves this state with a parametric quantum circuit. After that a correlational measurement is made on the output quantum state and a scalar is obtained. Gathering the scalar outputs, the final output of the quantum convolutional layer is a 3-dimensional array. Then a pooling layer is used to reduce the dimensionality of the data. This process could be repeated and finally ends with a fully connected layer. The single-qubit layer consists of Ry gates, each containing one tunable parameter. The two-qubit layer consists of CNOT gates on nearest-neighbour pairs of qubits

Concretely, the foreground pixels are represented by random floating numbers ranging from 0.7 to1, whereas the background are small floating numbers ranging from 0 to 0.1. There are 5 labels, namely *S, O, I, T* and *L,* each of which represents a type of Tetris bricks. The dataset is further processed by randomly splitting into a training set and a testing set that contain 80% and 20% of the images, respectively. This QCCNN was compared with CNN with two particular structures, namely one with a single convolutional layer and another with two convolutional layers. To see the performances with a different number of labels, researchers create another dataset by only picking the two labels *S, T* out of the original training and testing data. For the single-layer structure, they use a single (quantum) convolutional layer with 5 filters with no padding, plus a pooling layer also with no padding. For the two-layer structure, they use two (quantum) convolutional layers with 2 and 3 filters respectively, plus a pooling layer with padding 1. The window shape for all the layers is 2 × 2, and the stride value s = 1. Therefore, the number of qubits fed to the quantum filter is 4, and the depth of the parametric quantum circuit is set as 4. During 1000 iterations, it was computed the accuracy on the testing data and store the values of the loss function, which is chosen as mean square loss. In Figure A2.3 (a, c), researchers plot the accuracy and loss values for the 2-label case. While in Figure A2.3(b, d) they plot the accuracy and loss values for the 5-label case.

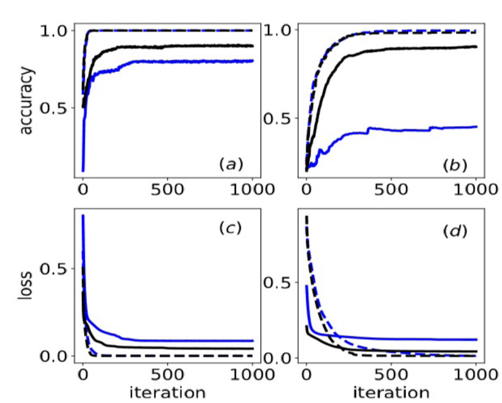

Figure A2.3. Accuracy and loss as a function of the number of iterations

Note: In all the *fi*gures the blue line represents the result of one-layer

CNN and the black line represents the result of two-layer CNN, the blue dashed line represents the result of one-layer QCCNN and the black dashed line represents the result of two-layer QCCNN. The results are averaged over 10 random simulations. (a) Accuracy in case of 2 labels. (b) Accuracy in case of 5 labels. (c) Loss in case of 2 labels. (d) Loss in case of 5 labels.

We can see that QCCNN can reach almost 100% accuracy for both the two structures they have used, and it can reach much lower loss values for both cases compared to its classical counterpart. Benefiting from the high-dimensional nature of the quantum system, the advantages of QCCNN become more transparent when the number of labels increases from 2 to 5. We can also see that the 5-label case takes more iterations to converge than the 2-label case, and that QCCNN with a two-layer structure converges faster than the single-layer structure, especially in the 5-label case, which indicates that for complex problems, better performance could be achieved by deeper architectures. In summary, researchers present a hybrid quantum-classical Convolutional Neural Network which could be used to solve real world problems with current quantum computers. As a quantum machine learning algorithm inspired by classical CNN, QCCNN keeps the features of CNN such as the nonlinearity, locality of the convolutional layer, as well as extensibility to deep structures. Moreover, the generalized feature map with a parametric quantum circuit is able to explore the correlations of neighbouring data points in a exponentially large linear space, hopefully allowing this algorithm to capture the patterns in the dataset more efficiently or precisely with a quantum computer.

In [60], authors have discussed the implementation of the fast Fourier transform (FFT) as a quantum circuit. The quantum version of the FFT (QFFT) is defined as a transformation of a tensor product of quantum states. The QFFT has been constructed by a combination of several fundamental arithmetic operators such as an adder, subtractor and shift operators which have been implemented into the quantum circuit of the QFFT without generating any garbage bits. One of the advantages of the QFFT is due to its high versatility: the QFFT are applicable to all the problems that can be solved by the conventional FFT. The frequency domain filtering of digital images is one of the possible applications of the QFFT. The major advantage of using the QFFT lies in its quantum superposition: multiple images are processed simultaneously (see Figure A2.4 as a conceptual image of quantum parallelism). It is even superior to the QFT when the number of images is sufficiently large. Thus, the QFFT will be a great help in the industries including security, healthcare, and marketing research, where numerous images are involved. In particular, we can create a high pass filter for edge detection (Figure A2.4).

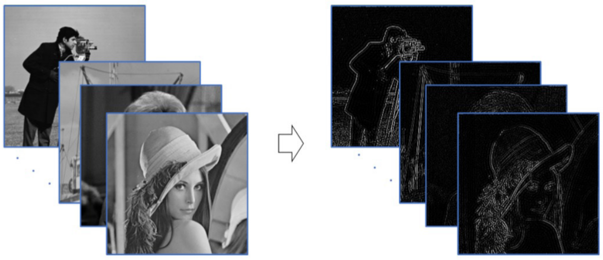

Figure A2.4. A conceptual image of the high pass filter applied to quantum multiple images

There are several issues remaining to be solved. The first one is how to effectively generate a quantum superposition of multiple data sets. Though, in principle, one can generate it using the Hadamard gate and the Pauli-X gate, it is still a difficult problem to superpose arbitrary data sets with arbitrary probability amplitudes. The second is how to use the resultant multiple data sets obtained by performing the QFFT. The QFFT sustains all the information of Fourier coefficients until the moment the quantum state is measured. If the quantum state that contains the Fourier coefficients of multiple data sets was passed on to some quantum device directly and there were some proper techniques to handle it, it would play a key role in the field of quantum machine learning.

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