Intelligent Control Using Integrated Cubic Neural Network

Kazuo Yoshida
Department of System Design Engineering Keio University
3-14-1, Hiyoshi, Kohoku-ku, Yokohama 223-8522, JAPAN
yoshida@sd.keio.ac.jp

***Abstract* — This paper introduces an intelligent control method using the cubic neural network where information processing is carried out for multiple purposes and multiple degrees of information abstraction. The cubic neural network consists of ordinary neural networks and their related fuzzy-neural networks obtained by abstracting their information processing. When this cubic neural network is utilized for systems control, the ordinary neural networks correspond to each controller for multiple purposes and their related fuzzy-neural networks are used for various nonlinearities and uncertainties including those due to fault of system, which are not taken into consideration at modeling process. The present intelligent control method using the cubic neural network has an integrator that selects and combines ordinary neural networks and fuzzy neural networks and is design by applying the genetic algorithm. The effectiveness and validity of the intelligent control method using cubic neural network are demonstrated through fundamental illustrations concerning pendulum dynamics and the other applications.**

I. Introduction

Recently, intelligent control methods such as fuzzy control and neural network control have been spreading and many researches on intelligent control method have been carried out especially in the field of robotics. The approaches of intelligent control have been adopted from various viewpoints of control designs. For instance, control objects are too complicated so that their modeling is difficult. And human knowledge is positively utilized for controller design. In fact, the concept of intelligent control was used by K. S. Fu [1] for the multi-disciplinary field of control and artificial intelligence, and the control without human operation which possesses the same ability as that with it was regarded as an intelligent control. This control is considered to be an alternative of human ability of making decision or strategy and learning a new function in uncertain and varying circumstances. Thus, based upon the human ability the intelligent control has been considered so far. J. Rasmussen [2] proposed that human cognitive behavior during motion is hierarchically divided into three phases of skill base, rule base and knowledge base. This model is named "Rasmussen cognitive model" and is well known as a typical hierarchical control structure.

G.N. Saridis [3] proposed an intelligent control possessing the hierarchical structures of organizer and coordinator of which principle is named "Increasing Precision with Decreasing Intelligence (IPID)". In this structure the abstraction is advanced in a higher level. On the other hand, control precision and response speed are high in a lower level. J. S. Albus [4] proposed a cerebella model articulation controller and extended it to a hierarchical control of robot manipulator. Furthermore, NASA/NBS Standard Reference Model (NASREM) was proposed [5] based upon that model for a real-time control system. NASREM consists of three main parts, task decomposition, world modeling and sensor processing. Each module possesses a hierarchical network structure. The global memory is data base where information of external world is stored and plays a role of aiding each module.

R. A. Brooks [6] proposed the subsumption architecture for an intelligent control referring to such autonomous system as insect, where module decomposition is performed for each purpose instead of function and parallel signal processing is carried out. For example, in case of mobile robot, signal processing from sensing to activating are independently performed for obstacle avoidance, wandering and searching in a hierarchical architecture of subsumption. This structure is characteristics of redundancy, extension ability and failure-proof, and is categorized into behavior based robotics, which attracts attention in the field of not only robotics, but also artificial intelligence, artificial life and so on.

T. Fukuda and M. Shibata [7] considered that the logical decision for control strategy which is suitable to environment and control of actuator is necessary for intelligent robot to perform the behavior similar to human one, and proposed a hierarchical intelligent control system. This system consists of learning level, skill level and adaptation level. For the adaptation level, a neural network is utilized and for the skill level, fuzzy-neural network is used, but in the case of modifying the objective value of adaptation level control logical inference requiring much time is not performed. In the low level the adaptation is performed in the bottom up manner by trial and error using the genetic algorithm and on the other hand, knowledge is acquired and renewed in the top down manner by using human instruction and evaluation.

The proposed intelligent control methods designed by expert systems or knowledge bases based upon past experience have a little ability to cope with unexpected states, although the subsumption architecture has such a function as its complementary function in a sense. However, the systematic synthesis approach of the architecture has not been given. In order to have an intelligent control possess such a function, this paper introduces a systematic approach of intelligent control using the cubic neural network (CNN) [8] that possesses a multilevel structure and uses parallel distributed signal processing. This intelligent control method is applied to a kind of high robust control problem of a fault-tolerant control and nonlinear control of multi-objective control problem. As the former applications, control problems of an inverted pendulum and a fluidized bed incinerators subjected to sensor fault and a structure subjected to nonlinear large deformation are introduced, and as the latter applications, swing up and stand up control of a single and double pendulum and prevention control of falling down of forklift and structural control are introduced.

II. INTELLIGENT CONTROL USING CUBIC NEURAL NETWORK

Based upon a hint from the reference [9], the author devised the cubic neural network in which the layered neural networks possess the same input and the higher layers deals with higher abstracted information. In other words, the lowest layer processes quantitative information and the other higher layers deals with different degrees of qualitative information. Therefore, such neural networks of qualitative information processing might correspond to rule-based information processing. And an evaluation network is added to each layer of the neural networks to evaluate its suitability to the environment autonomously.

In the intelligent control using the CNN which the author proposed as shown in Figure 1, the lowest level performs a quantitative control and its control performance is the highest in comparison with the other levels of controls, but the applicable region of the controller is the smallest. On the other hand, the higher levels perform qualitative controls and they are inferior to the lowest one, their applicable regions are larger than the lowest one as shown in Figure 2. The network which integrates the level of abstraction autonomously is also acquired by the genetic algorithm (GA).

The characteristics of the intelligent control using CNN is as follows:

(1) At normal situation of system, a quantitative controller of Level 1 controls the system precisely. In an abnormal state of system, qualitative controllers of which abstraction level is high control the system not precisely but stably in certain range.

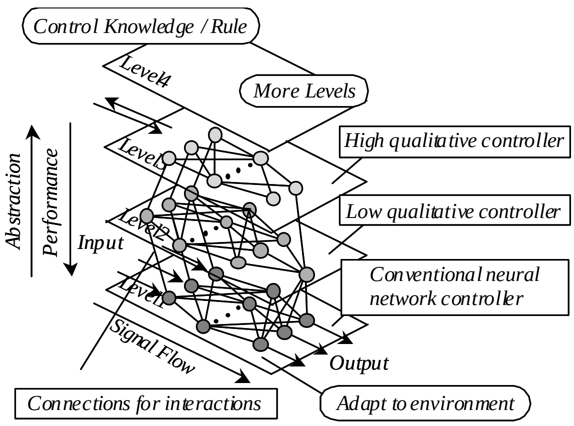


Figure 1 Intelligent control using cubic neural network

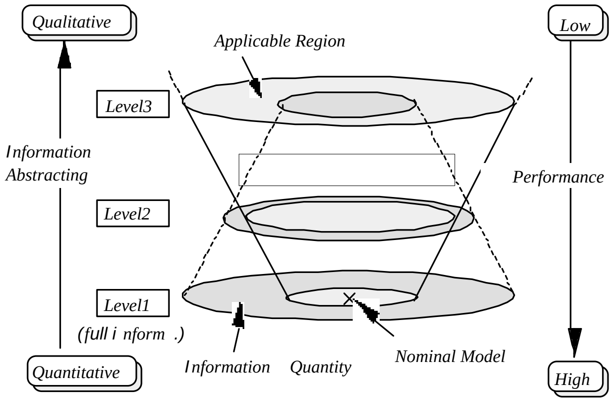


Figure 2 Features of cubic neural network control

(2) Since the intelligent control has the cubic structure of abstraction axis, the systematic synthesis is feasible and according to the necessity complementary controllers can be added.

(3) Qualitative controllers can be acquired by abstracting quantitative controllers in a learning manner.

(4) From the qualitative controllers control rules and knowledge can be acquired.

Level 1 controller which treats ordinary detected values performs quantitative control. In this case, an ordinary neural network synthesis is adopted for a level 1 controller. Hierarchical abstraction from the quantitative controller is carried out on the basic scheme of information representation and then qualitative controllers are obtained through the abstraction. As an abstraction method of quantitative information, the method of fuzzy neural network is used as shown in Figure 3. In this case, the input output characteristics of neural network controller designed by first level are learned with the fuzzy neural network. The abstraction is performed at the first hidden layer. In this manner, the control rules are abstracted maintaining the essential property of quantitative controller.

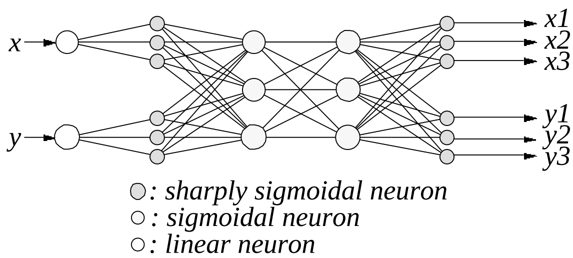


Figure 3 Abstraction performed by fuzzy neural network

In order to integrate quantitative and qualitative controllers, it is necessary to evaluate each layer network. In this method, the evaluation part is constructed by networks, as shown in Figure 4, of which inputs are the error between the output of a system neural network corresponding to the same level and the abstracted measured signals.

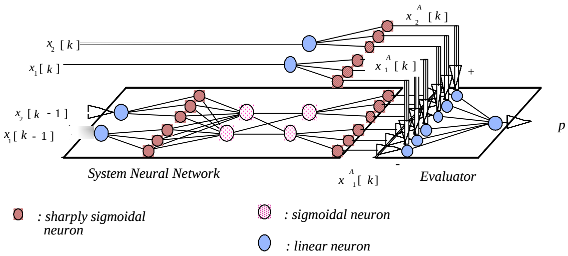


Figure 4 Abstracted system neural network and evaluator

III. FAULT-TOLERANT CONTROL BY CNN INTELLIGENT CONTROL

Here, the capability of coping with an abnormal situation of sensor is introduced. First, the stabilization problem of an inverted pendulum is considered for an abnormal situation of sensor, that is, it is supposed that something is wrong in a sensor of pendulum angle and results in the gain reduction of amplifier for sensing. According to the synthesis method of the intelligent control using cubic neural network, qualitative controllers are obtained through the abstracting of a qualitative controller. The qualitative controllers possess the control strategy inherent in the principle of stabilization of an inverted pendulum. The evaluators of each level are also designed and an integrator is obtained by applying the genetic algorithm. They are organized as shown in Figure 5.

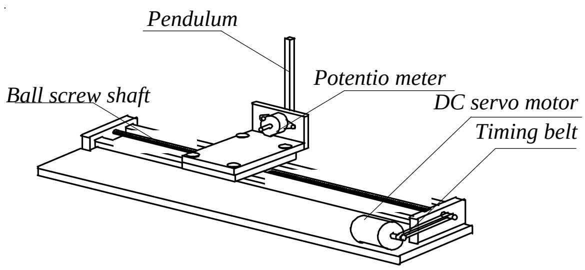


Figure 5 Experimental setup of an inverted pendulum

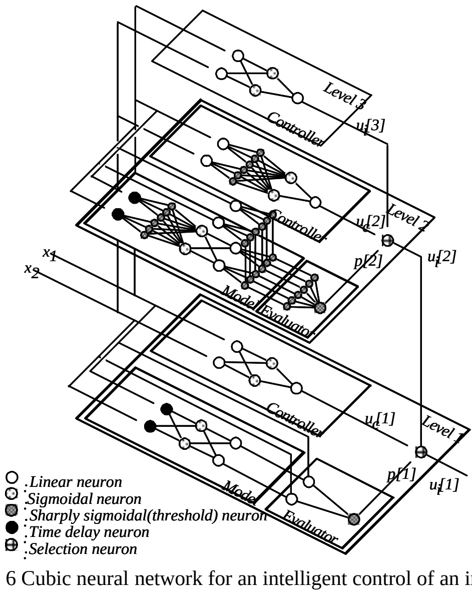


Figure 6 Cubic neural network for an intelligent control of an inverted pendulum

We consider an abnormal situation that abrupt reduction of the sensor amplification occurs. For such abnormal situation, the ordinary optimal control synthesized well for the pendulum can not stabilize the pendulum if the amplification goes down by 30 %. On the other hand, it was demonstrated in the experiment that the intelligent control using cubic neural network can stabilize it even if the amplification goes down by 90 %, that is, 1/10, since the integrator switches automatically the level of controller according to the result of evaluator.

Second, the fault tolerance performance of the CNN intelligent control is shown by applying the CNN intelligent control method shown in Fig. 7 to a control problem of a swung up and inverted pendulum mounted on a cart for the case that arbitrary initial condition of pendulum angle. In order to confirm the performance of the controller, experiments using a real apparatus were carried out for the cases of parameter variation and sensor fault. As a result, it was demonstrated that the controller can stand up the pendulum taking into account the cart position limit at abnormal situations. Then, the robustness and the fault- tolerance of the proposed CNN controller were experimentally verified [10] in comparison with the sliding mode control technique, as shown in Figs. 8 and 9. It is seen form these figures that the CNN intelligent control has much more robustness against parameter variation.

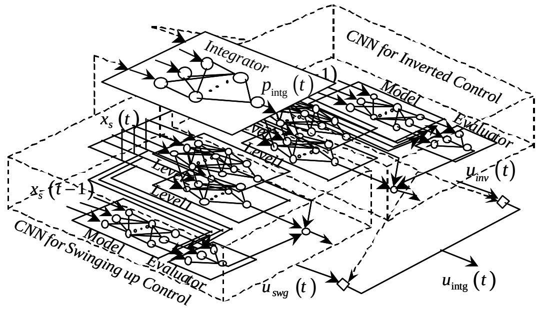


Figure 7 Cubic Neural Network for swung up and inverted pendulum

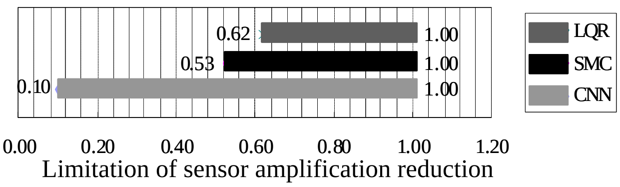


Figure 8 Experimental results with sensor fault.

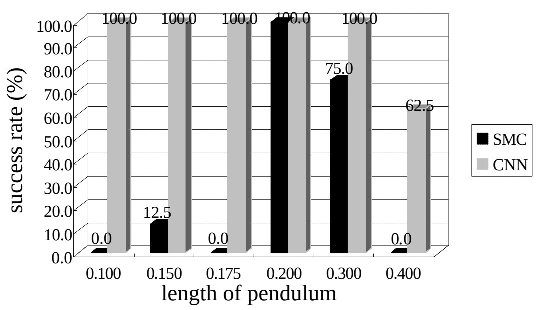


Figure 9 Experimental results with parameter variation.

Furthermore, in the application of the CNN control shown in

Fig. 10 to a double pendulum [11], it was demonstrated as shown in Fig. 11 that the CNN intelligent control is much superior to the optimal linear quadratic regulator (LQR) in the robustness against parameter variation.

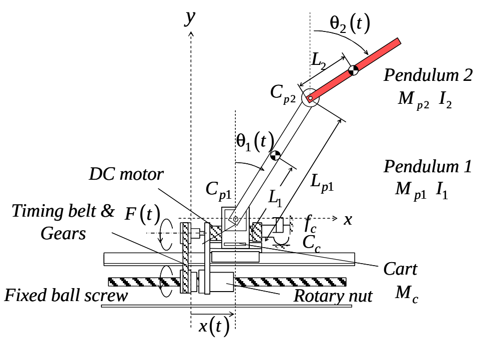


Figure 10 Double pendulum model

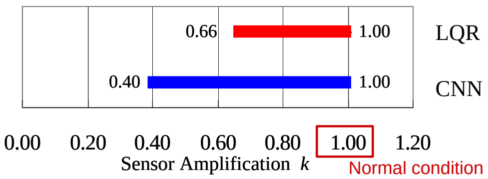


Figure 11 Experimental results of robustness

Next, we introduce the application [12] of CNN intelligent control to sensor fault problem in combustion control of fluidized bed incinerators, as shown in Figure 12, which can burn waste in a short time by stirring waste and fluidized sands. But, it is difficult to stabilize the plant without operators at abnormal situations and to obtain exact mathematical models. And they tend to change their characteristics. So, it is necessary for the plant control to realize an intelligent control method which stabilizes plants when abnormal situations occur, which are not only expected, but also unexpected and when their characteristics change. Figure 13 shows an example of scheme of CNN intelligent control for a fluidized bed incinerator. Figure 14 shows an example of response of real plant to sensor failure. In this figure it is supposed that the sensor amplification goes down up to 1/3 abruptly due to a sensor failure at the point indicated by an arrow, in other words, the temperature measured in incinerator goes down up to 1/3. From this figure, it is seen that CNN controller can stabilize the combustion and was verified by the experiment of a real plant.

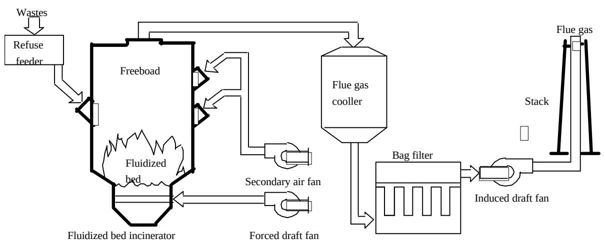


Figure 12 Fluidized bed incinerator

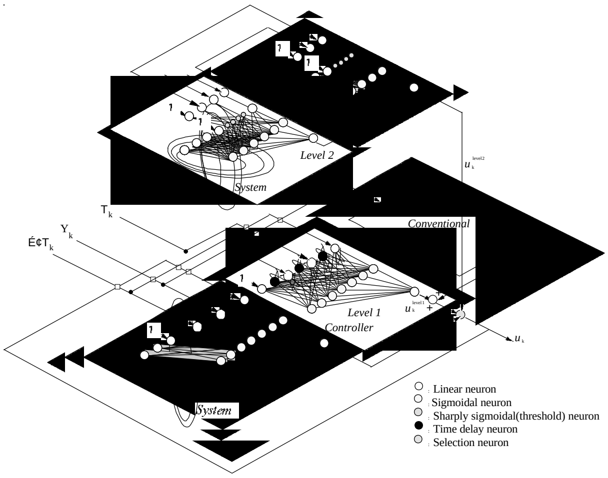


Figure 13 Scheme of CNN combustion control

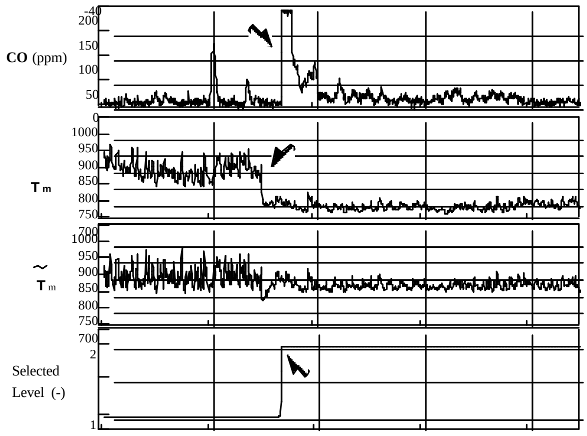


Figure 14 Example of response of real plant to sensor fault

Furthermore, we introduce an application example [13] of CNN intelligent control to the vibration controls of structure, as shown in Fig. 15, subjected to sensor fault, plastic nonlinearity of structure and so on. We suppose some cases that the amplifier amplification of acceleration sensor changes abruptly including the inverse phase change. Figure 16 shows the designed CNN intelligent controller in which the sensor fault concerning the amplification and the phase of sensor and the nonlinearity due to elasto-plastic deformation are taken into consideration.

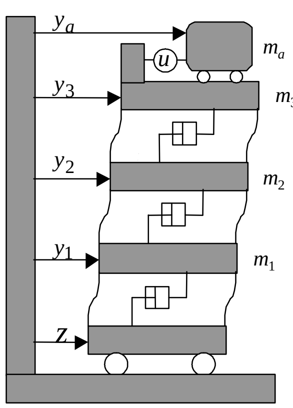


Figure 15 Application to fault-tolerant vibration control for structure

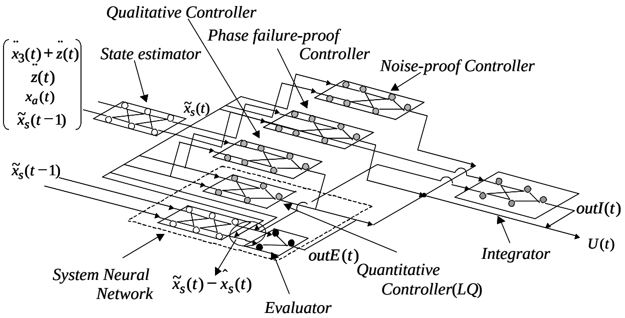


Figure 16 CNN intelligent fault-tolerant controller for vibration control

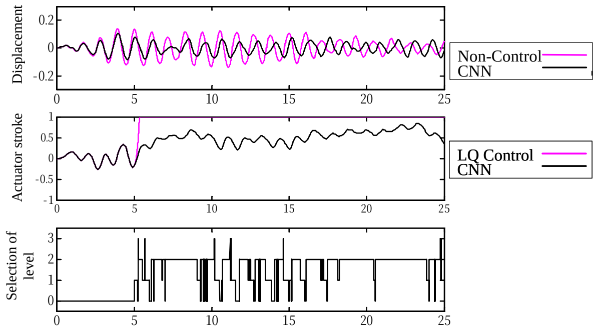


Figure 17 Time histories of CNN control for inverse change of sensor phase

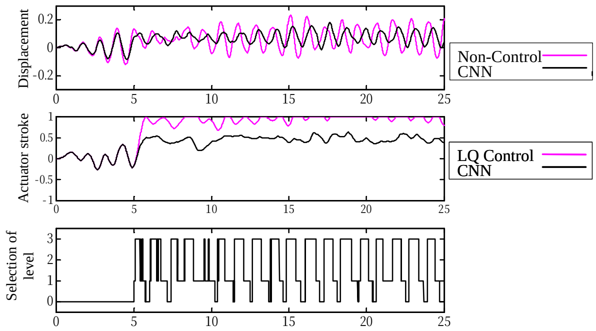


Figure 18 Time histories of CNN control for elasto-plastic nonlinearity

Figure 17 shows the time histories of the CNN intelligent control for the fault case that sensor phase changes abruptly into inverse in comparison with the non-control case and the LQ optimal control. It is seen that the stroke of active vibration absorber designed by the ordinary LQ optimal control diverges instantaneously, while the CNN intelligent controller shown in Fig. 16 maintains stability and performance to some extent. Figure 18 shows the time histories of the CNN intelligent control for the case that elasto-plastic deformation occurs in the structure. It is demonstrated that the CNN intelligent control maintains vibration suppression, while the LQ control can not control the vibration. From these figures, It follows that the CNN intelligent control possesses fault-tolerant property.

IV. Multi-objective control by CNN intelligent control

The basic architecture of CNN intelligent control for multi-objective control is shown in Fig. 19. In the architecture cubic neural network is constructed for each objective and they are integrated by an integrator. The before-mentioned problem of swinging up and stabilizing a pendulum is a kind of multi-objective controls. The intelligent controller using cubic neural network, as shown in Fig. 7, possesses the same architecture as the basic one shown in Fig. 19. For the multi-objective control, the integrator plays an important role in the intelligent control. The integrator switches several controllers autonomously and adequately depending on the system state. Additionally, the integrator integrates them and generates new control input to achieve a control objective. It is expected that the CNN intelligent control method enable us to accomplish several control targets by using less controllers and switching laws. Therefore, by illustrating an example [14, 15] of multi-objective CNN control for multiple targets of the equilibrium points of double pendulum which are shown in Fig. 20, the design method of the integrator is introduced in this chapter.

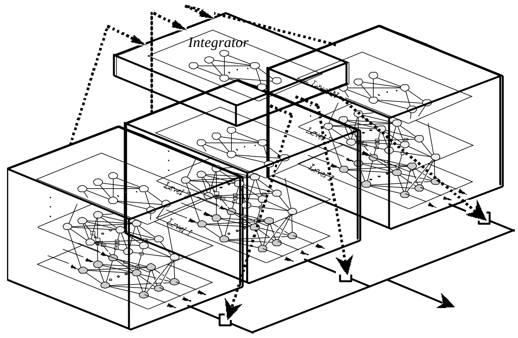


Figure 19 Basic architecture of integrated CNN

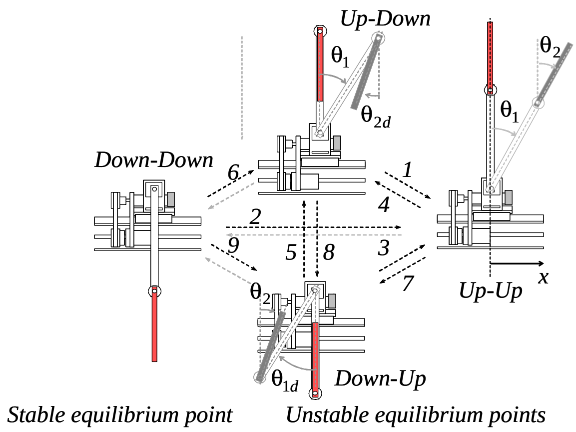


Figure 20 Multiple equilibrium points of double pendulum

Double pendulum has four equilibrium points as shown in Fig. 20. Here, we consider the application of the CNN intelligent control method to the transfer control problem of a double pendulum from an arbitrary equilibrium point to the other equilibrium points. This is considered to be a multi-objective control problem. In an example of using conventional nonlinear control method [16], twelve controllers and eleven switching rules were required to realize five paths. Figure 21 shows the integrator of CNN intelligent control designed for the transfer control problem. As shown in this figure, the number of controllers is only four, three stable controllers and one unstable controller. The integrator switches adequately the unstable controller and each stable controller. The parameter adjustment of the integrator is performed by a probabilistic optimization method utilizing the Genetic Algorithm (GA). In the optimization process, the energy principle is embedded into the neural network so as to maintain the robustness of control

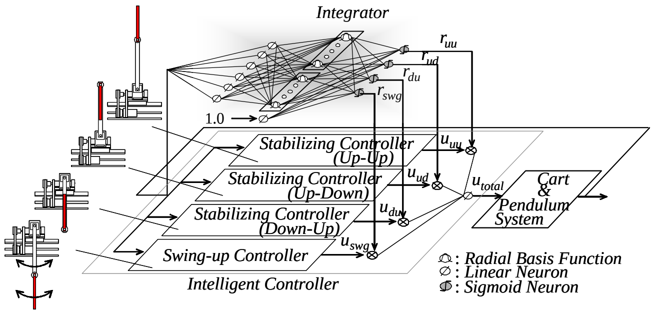
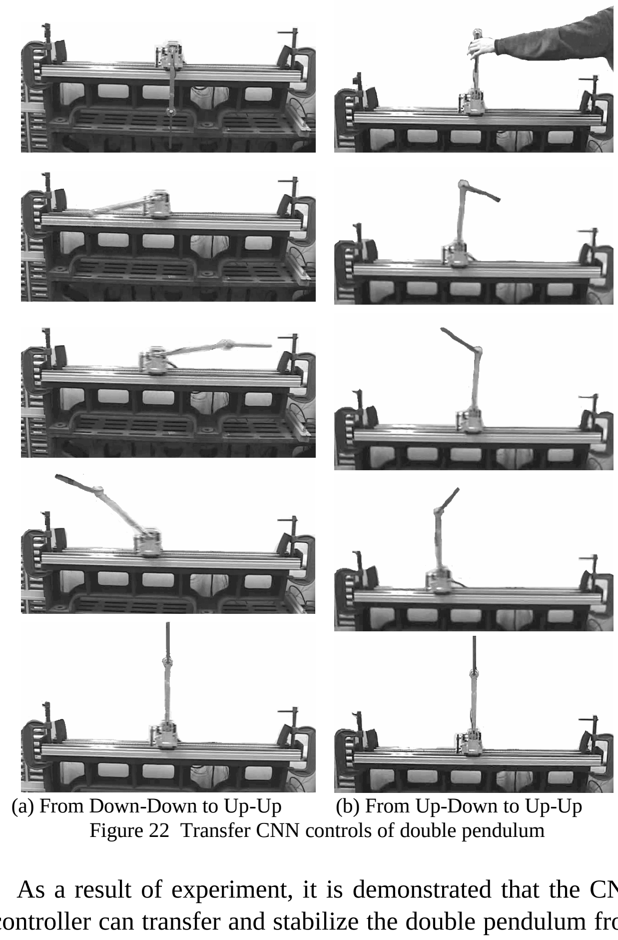


Figure 21 Integrated Intelligent Control System with an integrator


(a) From Down-Down to Up-Up (b) From Up-Down to Up-Up
Figure 22 Transfer CNN controls of double pendulum

As a result of experiment, it is demonstrated that the CNN controller can transfer and stabilize the double pendulum from an arbitrary equilibrium point to the desired unstable one. An illustration is shown in Fig. 22.

V. CONCLUSION

In this paper, an intelligent control method using cubic neural network was introduced. The effectiveness and the usefulness of CNN intelligent control for fault tolerant control and multi-objective control were demonstrated through the various applications.

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