

Chapter 9

Pavlovian, Skinner, and Other Behaviourists' Contributions to AI

Witold Kosinski and Dominika Zaczek-Chrzanowska
Polish-Japanese Institute of Information Technology, Research Center
Polsko-Japońska Wyższa Szkoła Technik Komputerowych
ul. Koszykowa 86, 02-008 Warszawa
wkos@pjwstk.edu.pl mado@pjwstk.edu.pl

Abstract

A version of the definition of intelligent behaviour will be supplied in the context of real and artificial systems. Short presentation of principles of learning, starting with Pavlovian's classical conditioning through reinforced response and operant conditioning of Thorndike and Skinner and finishing with cognitive learning of Tolman and Bandura will be given. The most important figures within behaviourism, especially those with contribution to AI, will be described. Some tools of artificial intelligence that act according to those principles will be presented. An attempt will be made to show when some simple rules for behaviour modifications can lead to a complex intelligent behaviour.

1. Intelligence: Description

It can be stated without any doubt that behaviourists have made a great contribution to the development of artificial intelligence. The evidence from the animal learning theory, especially the laws of learning discovered by behaviourists, has attracted researchers within artificial intelligence for many years and many models have been based on them.

Intelligence is a complex and controversial concept, therefore it is very difficult to capture it by a simple definition. According to Jordan and Jordan [1] it is appropriate to regard intelligence as a concept we employ to describe actions of a certain quality. Two criteria should be used in this regard, namely, speed (i.e. how quickly an agent performs a particular task requiring mental ability) and power (i.e. the degree of difficulty of the tasks an agent can perform). On the other hand one can find another definition of intelligence expressed in term of an ability to perform cognitive processes. There are three fundamental cognitive processes: 1) abstraction, 2) learning, and 3) dealing with novelty.

Intelligence has been given many definitions by prominent researchers in the field, for example, it has been defined as:

- A general ability which involves mainly the education of relations and correlates. (Spearman, 1904) [2]
- The ability to judge well, to understand well, to reason well. (Binet and Simon, 1905) [3]
- The capacity to form concepts and to grasp their significance. (Terman, 1916) [4]
- The ability of individual to adapt adequately to relatively new situations in life. (Pintner, 1921) [5]
- The power of good responses from the point of view of truth or fact. (Thurstone, 1921) [6]
- The mental capacity to automatize information processing and to emit contextually appropriate behaviour in response to novelty; intelligence also includes metacomponents, performance components, and knowledge-acquisition components. (Sternberg, 1986) [7]

There are two main approaches to describing intelligence: the psychometric approach and the information-processing. The psychometric approach focuses on measuring or quantifying cognitive factors or abilities that make up an intellectual performance. Those cognitive factors might include: verbal comprehension, memory ability, perceptual speed, and reasoning. The scholars who follow this approach either lump these factors together (lumpers) or split them apart (splitters).

According to lumpers, intelligence involves a general unified capacity for reasoning, acquiring knowledge, and solving problems. The most well-known theory is Spearman's two-factor theory [2]. Spearman proposed that intelligence consisted of two factors: a single general factor (g) and numerous specific factors (s). The performance in any test or task is a function of both g and s . The idea of general intelligence factors is behind using a single measure of intelligence, such as an IQ (intelligence quotient) score.

In contrast to lumpers, splitters define intelligence as composed of many separate mental abilities that function more or less independently. According to well know Gardner's multiple-factor theory [8], there are at least seven independent aspect of intelligence: verbal skills, math skills, spatial skills, movement skills, musical skills, insight about oneself, and insight about others. Gardner stated that understanding these aspects comes from studying person in his or her environment and not from results of IQ tests.

The competitive approach to intelligence—information-processing approach—defines intelligence by analyzing the components of the cognitive processes that people use to solve problems. The well-known example of this approach is Sternberg's triarchic theory [7]. Sternberg proposes that intelligence can be divided into three ways of gathering and processing information. The first uses analytical or logical thinking skills that are measured by traditional intelligence tests. The second uses problem-solving skills that require creative thinking, the ability to deal with novel situations, and the ability to learn from experience. The third is using practical thinking skills that help a person to adjust to and to cope with his or her sociocultural environment.

Although experts provide us with many definitions of intelligence they tend to agree that intelligence is: (1) the capacity to learn from experience and (2) the capacity to adapt to one's environment.

Not only defining intelligence but also its measurement it is a very controversial topic. The first systematic attempt to measure intelligence was made in the beginning of this century by Alfred Binet. Binet-Simon Intelligence Scale [3] contained questions that measured vocabulary, memory, common knowledge, and other cognitive abilities. Binet also introduced the concept of mental age, which became the base for computing intelligence quotient (IQ). According to him, mental age is a method of estimating a child's intellectual progress by comparing the child's score on an intelligence test to the scores of average children of the same age. Several years later Terman [4] proposed a formula to calculate IQ score. Intelligence quotient is computed by dividing a child's mental age (MA), as measured by an intelligence test, by the child's chronological age (CA) and multiplying the result by 100. Nowadays, the most widely used IQ test for adult are: Stanford-Binet tests and Wechsler Adult Intelligence Scale-Revised (WAIS-R) [9].

2. Artificial Intelligence

Traditional AI and cognitive science proceed by developing computer models of mental, human-like, functions. As a consequence, intelligence in these disciplines is closely tied to computers, it can be understood in terms of computer programs. When input is provided, input is processed, and finally output is generated. Then by analogy the human brain is viewed in some sense as a very powerful computer, as a seat of intelligence (Pfeifer & Scheier, 1999), [10]. However, when researchers in AI started applying these ideas to build robots that interact with real world, they found that it was rather difficult to have robots doing good jobs with this view of intelligence.

There are several frequent criticisms of classical AI:

- Classical AI systems *lack generalization capabilities*: Complete systems cannot be made from studies of isolated modulus.
- Classical AI systems *lack robustness* and cannot perform in real time, and run on sequential machines.
- Classical AI systems are *goal based* and organized *hierarchically*; their processing is done *centrally*.
- The real world differs from *virtual ones*: It has its own dynamics. The virtual world used in A.I. systems has states with *complete information* on them, they are *static*.
- *The frame problem appears*, i.e. how can models of parts of the real world *be kept in tune* with the real world as it is changing, and how can systems *determine* which changes in the world are *relevant to* a given situation without having to test all possible changes.

Many started looking for alternatives, and it was R. Brooks from MIT [11] who maintained that all of AI's ideas concerning thinking, logic, and problem solving were based on assumptions that come from our own introspection, from how we see ourselves. We have to focus on the interaction with the real world: Intelligent behaviour could be achieved using a large number of loosely coupled processes that function predominantly in an asynchronous, rather parallel way. This was an origin of his *subsumption architecture*. He called his new paradigm in the study of intelligence "behaviour-based robotics." (cf. Arkin, 1998) [12]. Now one often refers to the field as embodied cognitive science. Subsumption is a method of decomposing a robot's control architecture into a set of task-achieving behaviours or competences. One should add at this point

that the term behaviour is used here in two ways, in the first, more informal use, behaviour is the result of a system-environment interaction, while in the second, more technical sense, behaviour refers to internal structures, i.e. the particular layers of modules designed to generate particular behaviours (in the first sense).

In the classical AI's approach control architecture for mobile robots is functional decomposition. First information from different sensor systems is received and integrated into a central representation. Then internal processing takes place in which an environment model (world model) is built or updated together with planning of the next actions. (Here decisions concerning further actions are made.) The final stage is execution of some actions. Altogether such an appraisal leads to the *sense-think-act cycle* and the thinking act is split into a modelling and a planning activity.

In the behaviour-based robotics the main role is played by a method of decomposing a control system of a robot into a *set task-achieving behaviours* (or *competences*). This was called by R. Brook the subsumption architecture, in which control architecture is build by incremental adding competences on top of each others. This method is contrasted with the classical AI's functional decomposition. Implementations of such task-achieving behaviours are called layers: higher-level layers build and rely on lower-level ones; instead of a single information process from perception to world modelling and action, there are multiply paths, the layers that are active in parallel. A series of small subtasks of the robot's overall task are not controlled in a hierarchical, traditional way, since each layer can function relatively independently; the subsumption approach realizes the direct coupling between sensors and actuators, with only limited internal processing. In this way a direct influence of young behaviourists approach is manifested.

In a modern encyclopaedia one can read that AI is an interdisciplinary field combining research and theory from cognitive psychology and computer sciences, and which is focused on the development of artificial system that display human-like thinking or "intelligence." In other references AI is understood as any synthetic intelligence, i.e. the goal of the field of study in the above-described interdisciplinary domain. We will omit the term AI and use rather embodied AI to underline this new point of view.

3. Behaviourism

Behaviourism is considered as one of the major schools of thought in the history of psychology. This approach emphasizes the objective, scientific analysis of observable behaviours to the exclusion of consideration of unobservable mental processes. It studies how organisms learn new behaviours and change or modify existing behaviours in response to influence from their environments. The basic assumption of behaviourism is that learning is the most important factor in the development of human behaviour and the formation of personality. According to behaviourists learning is based on association between stimulus (S) and response (R) to it.

John Watson (1878-1958) is usually regarded as the father of behaviourism. According to him psychology is a purely objective experimental branch of natural science. Its theoretical goal is the prediction and control of behaviour. His ideas, published in 1913 in paper titled "Psychology as a Behaviourist Views It" [13] marked the beginning of the behavioural approach in psychology.

Although the founding of behaviourism is usually linked with the name of John Watson, many of the basic principles had already been published before Watson's time by a group of Russian researchers, in particular Ivan Petrovich Pavlov (1849-1936). In 1904 he won a Nobel Prize for his studies on the reflexes involved in digestion. But it was his discovery of conditioning, by which he made a considerable impact on the development not only psychology, but also AI [14].

The next person who made great contribution to the development of psychology and AI was Burrhus Frederic Skinner (1904-1990). He constructed a radical behaviourist theory in which behaviour is explained as the lawful result of environmental factors. Skinner is especially famous for the study of a form of learning known as operant conditioning [15].

The next three scientists who had a great impact on the development of behaviourism were Edward Lee Thorndike (1874-1949), Clark L. Hull (1884-1952) and Edward Chace Tolman (1886-1959). Their theories can be described as a 'subjective' behaviourism, because they moved away from the Skinner's radical behaviourism and in their explanation they refer to certain processes which take place within the organism.

Thorndike was particularly known for his extensive research into learning in animals and his attempt to develop a theoretical explanation for learning phenomena [16]. He initially described a form of learning known as trial-and-error learning or instrumental conditioning (Skinner used basically the same form of conditioning, but called it operant conditioning).

Hull is credited with developing the first systematic theory of learning known as the drive reduction theory [17]. According to his theory, it is drive and need that motivate to behave in a particular way.

According to Tolman [18], behaviour is largely regulated by cognitive factors such as the perception of signs and patterns in the environment, and the expectation of reward. Tolman can be regarded as a precursor of the social cognitive learning theory [19].

Social cognitive learning theory [20] agrees with other behaviouristically oriented theories in regarding behaviour as primarily learned and in focusing on the study of observable behaviour. However, there is a major difference because the social cognitive theory uses unobservable matters such as thoughts, expectations, and motivation in its explanation of behaviour. According to this school, the observational learning is the most important method of learning. Three psychologists, namely Julian Rotter, Albert Bandura and Walter Mischel are widely regarded as the most important figures in the development of social cognitive learning theory.

4. Learning

Learning can be defined as relatively permanent change in behaviour (both mental events and overt behaviours) that results from experience. Learning has taken place when a person or an animal has acquired knowledge of something that was previously unknown to him, or when he can do something he previously could not do.

The main types of learning that have been already identified and described can be classified on the basis of two criteria:

- The degree of understanding a learner must have of what is being learnt;
- The level of awareness on which learning takes place.

Two approaches to study learning have been used: association learning and cognitive learning.

In the association approach to learning, stimuli and responses are units on which the analysis of behavioural changes is based. The aim is to establish what the relationship is between a stimulus (S) and the human or animal organism's response (R) to it. There are two main types of association learning:

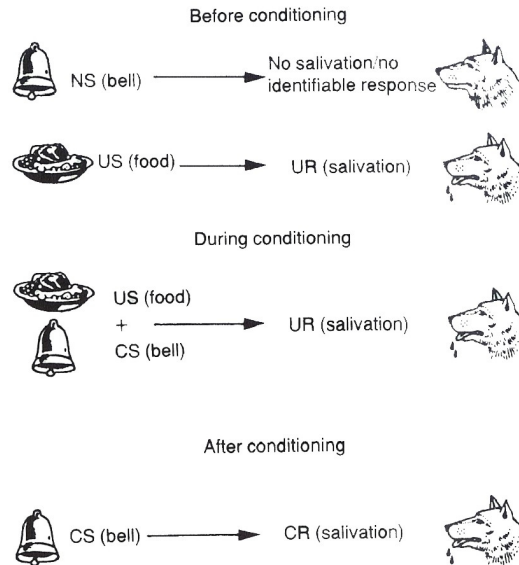
- Classical conditioning – I. P. Pavlov (1927);
- Operant conditioning – E.L. Thorndike (1913) [21] and B.F. Skinner (1969).

4.1 Classical Conditioning

Classical conditioning it is a kind of learning in which a neutral stimulus acquires the ability to produce a response that was originally produced by different stimulus.

The Russian physiologist Ivan Pavlov (1848-1936) is the father of classical conditioning. Pavlov first discovered that reflex of salivation and the secretion of gastric juices in a dog occur not only when food is placed in the dog's mouth, but also when the dog sees the food. He became interested in this phenomenon (Figure 1). In an experimental situation food was placed in a dog's mouth. Salivation occurred—salivation is a natural, reflexive and thus non-learned response to the stimulus (food). It occurred every time when food is given to the hungry dog. This response was named unconditioned response (UR). Pavlov then rang a bell close to the dog but as it was expected no salivation occurred. The sound of the bell is a neutral stimulus (NS). Later, Pavlov rang a bell before putting food in the dog's mouth. Salivation occurred. After a number of instances of hearing a bell paired with food, Pavlov again rang the bell, but he did not give food to the dog. Salivation occurred. In this situation salivation was elicited by the sound stimulus. Pavlov called this phenomenon a conditioned response (CR). The new S-R relationship (the relationship between the sound of the bell and salivation) is a consequence of the learned association between two stimuli (the bell and the food).

During classical conditioning, a dog not only learns to salivate to a tone but also simultaneously learns a number of other things that Pavlov identified as being a part of the classical conditioning procedure. The most important of them are: generalization, discrimination, extinction, and spontaneous recovery.



Classical conditioning.

Figure 1. The process of Pavlovian classical conditioning. After [1]

Nowadays there are two explanations of classical conditioning: The traditional and modern.

Pavlov's traditional explanation is known as stimulus substitution. According to stimulus substitution, a bond or associations forms between the conditioned stimulus and unconditioned stimulus so that the conditioned stimulus eventually substituted for the unconditioned stimulus. Rescorla's modern explanation [23] is called stimulus information. According to the information theory of classical conditioning, an organism learns a relationship between two stimuli such that the occurrence of one stimulus predicts the occurrence of another.

4.2 Operant Conditioning (OC)

Operant Conditioning [9] it 'is a kind of learning in which the consequences that follow some behaviour increase or decrease the likelihood of that behaviour occurring in the future. In OC an organism (agent) acts or "operates" on the environment in order to change the likelihood of the response occurring again' (p.214).

The first steps in the development of operant conditioning are found in the work of Thorndike [21]. He formulated the law of effect, which stated that behaviours (goal-directed) followed by positive consequences are strengthened, while behaviours followed by negative consequences are weakened. Thorndike's ideas were further developed and expanded by Skinner. In a typical Skinner experiment a hungry pigeon is placed in a Skinner box. The pigeon walks around in the box, pecking here and there. Eventually the pigeon pecks against the lighted window and food falls into the bowl. By pecking against the lighted window the pigeon "operates" on its environment. Therefore this response is called an operant response. The food is the reward or reinforcer, which reinforces the appropriate response and increases the likelihood that pigeon will perform that behaviour in the future. After the reinforcer is presented a number of times,

immediately upon the appropriate pecking response, the probability of the pecking is greater than any other response. The procedure of behavioural shaping can be used in conditioning the pigeon to pick against the window. During shaping, the experimenter reinforces behaviours that lead up to or approximate the desired behaviour. The progress of operant conditioning can be divided into two phases (Figure 2 and 3).

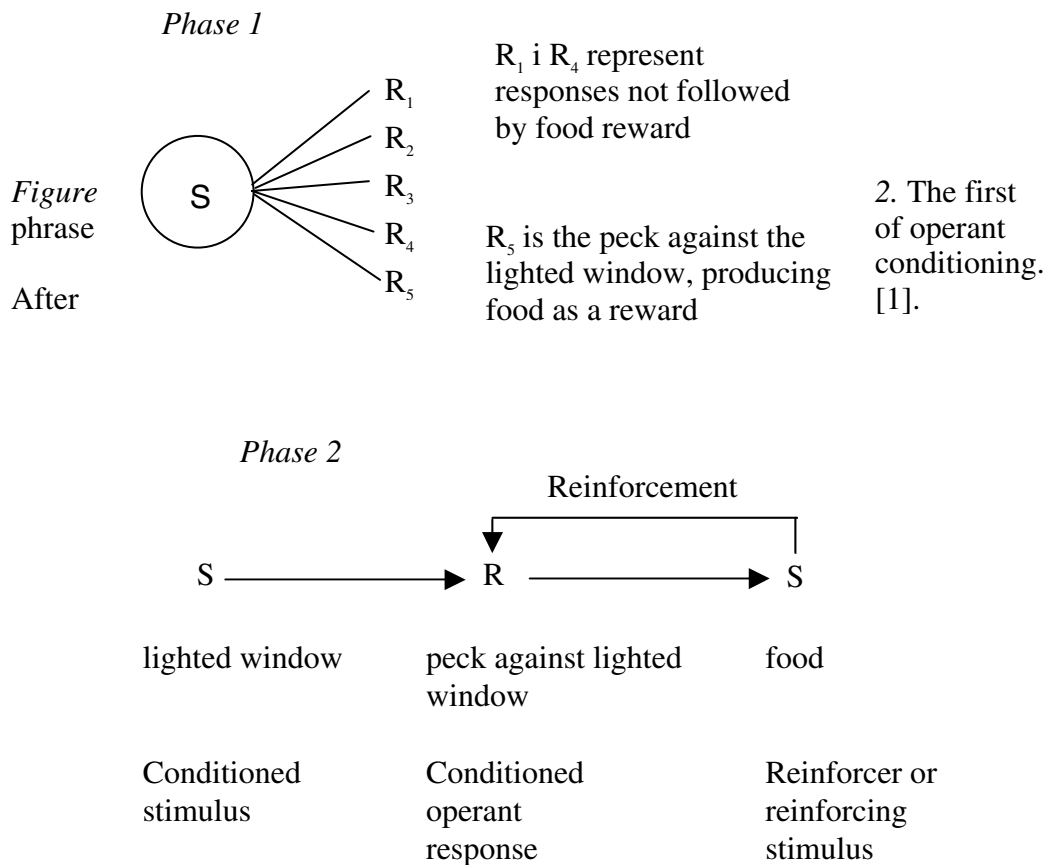


Figure 3. The second phrase of operant conditioning. After [1].

The first phrase corresponds to trial and error learning, in the sense that the pigeon produces the correct response by accident. The second phrase relates to the maintenance of the accidentally discovered correct response in accordance with the principle of reinforcement.

Operant conditioning focuses very sharply on the manipulability of behaviour. By manipulating the environmental conditions under which learning takes place, control can be exercised over the type and strength of behaviour that is learned. The essentials of operant conditioning can be summarized in five words—consequences are contingent on behaviour. There are two kinds of consequences—reinforcement and punishment. Reinforcement is a consequence that increases the likelihood of a behaviour occurring again and punishment is a consequence that decreases the likelihood of a behaviour occurring again. In addition, reinforcement can be either positive or negative. Positive reinforcement is a pleasant stimulus that increases the likelihood of a response occurring again. Negative reinforcement is the removal of an unpleasant stimulus, thereby increasing the likelihood of a response occurring again.

4.3 Cognitive Learning

Cognitive learning cannot be explained on the basis of reinforcing conditions. It is a kind of learning that involves mental processes, such as attention and memory, and may not involve any external rewards or require the person to perform any observable behaviours. Learning through thinking does not exclude the principles of association, however, it is regarded as a conscious act of thinking. There are two main kinds of cognitive learning:

- Sign/latent learning – E.C.Tolman (1932) [18],
- Observational learning – A.Bandura (1986) [23].

4.3.1 Sign/Latent Learning

According to Tolman, learning is attributed to the discovery of which response leads to what effect, and to a learned expectation that a certain stimulus will be followed by another stimulus. The stimuli are processed within the organism into an organized cognitive structure (cognitive map). The cognitive map is an organism's perceptual impressions of a learning situation. The performance of a correct response is a product of cognitive processes. Tolman also showed that organisms can learn in an absence of reinforcement—incidental learning. Bandura has developed Tolman's ideas.

4.3.2 Observational Learning

Bandura is a father of observational learning. It is a form of learning that develops through watching and does not require the observer to perform any observable behaviour or receive a reinforces. There are four components of observational learning: acquisition, retention, performance and reinforcement.

After describing the learning approaches the major differences between associative and cognitive learning are summarized now. Associative learning (behavioural approach) provides means of describing how a person or animal learns a series of correct or desired responses, it a kind of learning which demands little more than parrot-like repetitions under reinforcing conditions.

Cognitive learning explains learning with understanding and insight. Learning situation and material are perceptually organized by the learner, and then he formulates concepts and rules, next he recognizes the information so obtained into new and significant patters of information.

As a summary of learning, following Balkenius [24], we could present the main explanations of biological (animal) learning. According to those explanations the animal learns:

- Stimulus-response associations
- Stimulus-approach associations
- Place-approach associations
- Response chain
- Stimulus-approach chain
- Place-approach associations
- S-R-S' associations
- S-S' associations

However, we are not going to develop these aspects here.

5. Models of Behaviourists in AI

Robot learning in most cases is a kind of associative learning and differs widely, and ranges from the model of classical conditioning to reinforcement learning. Classical conditioning in robot learning is formed in the paradigm of unsupervised learning, for which learning rules are similar to *Hebb rules* or *Kohonen* ones. The Hebb rule [25] states that when a node (neuron) i repeatedly and persistently takes part in activating another node (neuron) j , then i -th neuron's efficiency in activating j -th neuron is increased. For example if a_i and a_j are the activations of the neuron i and j , respectively, and \bullet is the learning rate, while w_{ij} is the connection weight (efficiency weight) between the neuron i and j , then the weight change Δw_{ij} is

$$\Delta w_{ij} = \bullet a_i a_j \quad (1)$$

Hebbian learning has the advantage of being simple and based only on local communication between neurons: no central control is required. If a mobile robot, an agent, has been equipped with proximity and collision sensors as well as with a motor and wheels, the following so-called *distributed adaptive control architecture* can be interpreted in terms of classical conditioning (Figure 4).

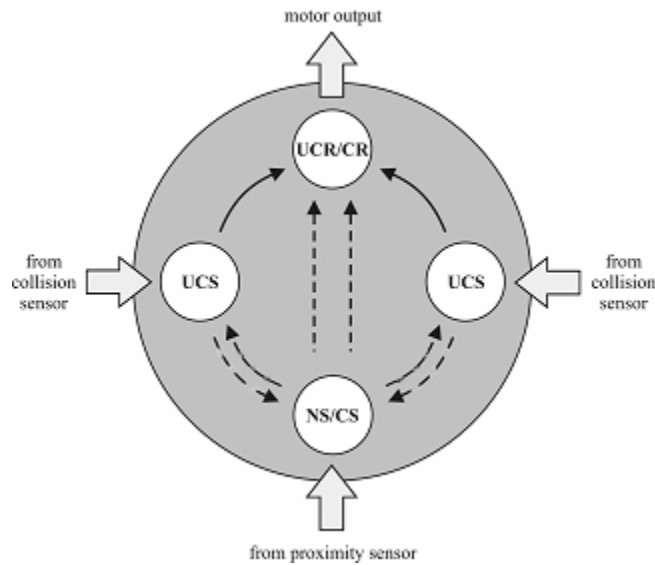


Figure 4. Distributed adaptive control architecture interpreted in terms of classical conditioning. after [10].

6. Distributed Adaptive Control

If a robot hits an obstacle as illustrated in Figure 4, activating a collision sensor, it backs up a little, turns and moves forward. Each sensor is connected to a node in the neural network: the collision sensors to nodes in the collision layer, the proximity sensors to nodes in the proximity layer. Moreover, the proximity layer is fully connected to the collision layer in one direction, while the collision layer is connected additionally to a motor output layer. The latter connections implement the basic reflexes, i.e. motor responses, called (in the Pavlovian approach) unconditioned response (UCR). The conditioned stimuli (CS) are the activations of the proximity sensors and the activations of the collision sensors model the unconditioned stimuli (UCS); they cause the robot to turn away from obstacle. We see that the UCS's are connected to the UCR's. (In Figure 4 collision sensors shown from both sides correspond to two sides of robots: the left side and the right one. The UCS - UCR connections are different for different sides since in one case turn in left, in the other turn in right, are executed to omit obstacle.) Note that before conditioning activation of proximity sensors (NS) did not cause any response (no action of motor devices). The conditioned response (CR), should, according to the Pavlovian approach, be very much like UCR; in the present (robot) situation it is not only similar to the UCR but in fact identical. (Notice that in Pavlov's experiments the neutral CS (bell) was paired with a UCS (food) that reliably produced UCR (salivation), and after some trials the bell was sufficient to produce salivation (the CR).)

If at time t the robot hits an obstacle the corresponding node (neuron) in the collision layer is turned on, and simultaneously in several proximity nodes are activated. Then through Hebbian learning at the next time step $t+1$ (cf. Eq. (1)) the corresponding connections between the proximity nodes (CS) and the active collision node (UCS) ($\Delta w_{ij} = w_{ij}(t+1) - w_{ij}(t)$) are strengthened. (In Figure 4 the learning stage is schematically presented by two curved arrows

pointing the bottom of the robot- NS/CS node.) This means that next time more activation from the CS nodes will be propagated to the UCS node. (Notice that when a collision appears the UCS nodes activate the UCR nodes in the motor output layer, and the robot backs up and turns to omit the obstacle.) If nodes in the collision layer (UCS) are binary threshold then after several hints due to the Hebbian rule of learning the activation originating from the CS layer becomes strong enough to raise the UCS node above threshold without collision initiating the activation the robot motor to avoid obstacles. (On Figure 4 this is schematically represented by two broken arrows pointing the top of the robot—the UCR/CR node.) When this happens the robot has learned to avoid obstacles through principle of classical conditioning [10].

Unsupervised learning paradigm known as a Kohonen map (or network) is used by a robot for location recognition, for example during which it measures the time between turn actions and hence it learns to recognize a particular location by building simple internal representations of its environment by a process of self-organization (without using explicit world model). In contrast to the previous distributed adaptive control, learning in the Kohonen algorithm is not incremental.

On the other hand operant learning in robot learning is formed in the paradigm of self-supervised learning. Here learning is based on reward (or punishment) resulting from behaviour. This is some-how similar to the operant conditioning of Thorndike and Skinner. Then two methods are distinguished, the first is that known in psychology as reinforcement learning, the other—as value-based learning. Value-based learning is learning modulated by a value system, which places some values on various types of sensory-actuator (motor) coordinations (i.e. value systems are activated only after an agent has performed behaviour. Both, however, methods employ principles of self-organization. The value system providing a kind of basic motivation for the agent guides the process of self-organization.

The third approach to learning is just teaching, and then we face with supervised learning or error-directed learning. For artificial, autonomous agent, such as neural networks that are models of human model behaviour, the delta rule, or more general, the error back-propagation rule are examples of learning rules. Often one says that supervised learning seems to resemble the way a mother teaches her child: The child can use the teaching signal from the mother to adjust his (her) responses. It is done by means of a supervised learning scheme in which the feedback from the mother has to be translated into error signals. However, this translation implies rather complex perceptual problems.

7. Conclusions

Following the point of view of the authors of [10] we can state that the complex intelligent behaviour can be performed by complete system (agent). According to them it should satisfied the following conditions:

- Complete system (agent) must possess the architecture:
 - with direct *coupling* of perception to action
 - with *dynamic interaction* with the environment
 - with intrinsic mechanisms to *cope* with resource limitations and incomplete knowledge
 - with *decentralized* processing

- Complete system has to be the *autonomous agent* (self-sufficient agent, equipped with the appropriate learning mechanism, with its own history, adaptive)
- Complete system has to be the situated *agent* (it acquires information about its environment only through its sensors and interacts with the world on its own)
- Complete system has to be *embodied* (it must interact with its environment, is continuously subjected to physical forces, to energy dissipation, to damage, to any influence in the environment)
- Complete system is behaviour based, not goal based
- Complete system includes sensors and effectors
- Sensory signals (stimuli) should be mapped (relatively) directly to effect or motors (responses)
- Complete system is equipped with a large number of parallel processes connected (only loosely) to one another

This leads to *embodied cognitive sciences* and to *embodied intelligence* introduced by Rodney Brooks [1991] and the *subsumption architecture*.

Since complete (i.e. intelligent) systems are behaviour based the behaviourists contributions are obvious.

Acknowledgement

The first author (W.K.) would like to thanks Mrs. and Mr. A. Adamkiewicz for the inspired discussions on psychology during his stay in their Dom na Ł kach in Izby, Beskid Niski Mountains, in the summer 2003. The help of Dr. Piotr Goł bek in collecting materials used in the preparation of the paper is highly acknowledged. The authors own a lot to Professor Rolf Pfeifer from Stuttgart and his excellent *AI-lectures from Tokyo* he gave in the winter semester of 2003/2004 via a tele-conference system (and Internet) from Tokyo simultaneously to Zurich, Muenchen, Beijing and Warsaw.

References

- [1] Jordaan, W., Jordaan, J. (1994). *Man in Context*. Lexicon Publishers, Isando
- [2] Spearman, C. (1904). General intelligence, objectively determined and measured. *American Journal of Psychology*, 15, 201-293
- [3] Gregory, R. J. (1996). *Psychological testing. History, principles and applications*. Allyn & Bacon
- [4] Terman, L.M. (1916). *The measurement of intelligence*. Boston: Houghton Mifflin.
- [5] Pintner, R. (1921). Intelligence. In E.L. Thorndike (Ed.). *Intelligence and Its measurement: A Symposium*. *Journal of Educational Psychology*, 12, 123-147 and 195-216
- [6] Thurstone, L.L. (1921). Intelligence. In E.L. Thorndike (Ed.). *Intelligence and Its measurement: A Symposium*. *Journal of Educational Psychology*, 12, 123-147 and 195-216
- [7] Sternberg, R.J. (1986). *Intelligence applied: Understanding and increasing your intellectual skills*. S Diego, CA: Harcourt Brace Jovanovich
- [8] Gardner, H. (1983). *Frames of mind: The theory of multiple intelligence*. New York: Basic Books
- [9] Plotnik, R. (1993). *Introduction to Psychology*. Brooks/Cole Publishing Company, Pacific Grove, California
- [10] Pfeifer, R., Scheier, Ch. (2001). *Understanding Intelligence*. MIT Press, Cambridge, Massachusetts, London, England
- [11] Brooks, R.A. (1991). Intelligence without representation. *Artificial Intelligence*, 47, 139-160
- [12] Arkin, R.C. (1998). *Behavior-based robotics*. Cambridge, MA: MIT Press
- [13] Watson, J.B. (1913). Psychology as the behaviorist views it. *Psychological Review*, 20, 158-177
- [14] Pavlov, I.P. (1927). *Conditioned reflexes*. London: Oxford
- [15] Skinner, B.F. (1969). *Contingencies of reinforcement*. New York: Wiley
- [16] Thorndike, E. L. (1911). *Animal Intelligence*. Hafner, Darien, Conn
- [17] Hergenhahn, B.R. (1984). *An introduction to theories of learning (2 ed.)*. Eglewood Cliffs, NJ: Prentice-Hall
- [18] Tolman, E. C. (1932). *Purposive Behavior in Animals and Men*. Century, New York
- [19] Brennan, J.F. (1982). *History and systems of psychology*. Eglewood Cliffs, NJ: Prentice-Hall
- [20] Schults, D. (1990). *Theories of personality (4ed.)*. Monterey, CAL: Brooks/Cole
- [21] Thorndike, E.L. (1913). *Educational psychology: The psychology of learning, vow.2*. New York: Teachers College
- [22] Rescorla, R.A. (1988). Pavlovian conditioning. *American Psychologist*, 43, 151-160
- [23] Bandura, A. (1986). *Social foundations of thought and action*. Englewood Cliffs, NJ: Prentice Hall
- [24] Balkenius, Ch. (1994). Biological learning and artificial intelligence. *Lund Univerisity Cognitive Studies*, 30, 1-19
- [25] Hebb, E.O., (1949). *The organization of behavior*, New York: John Wiley and Sons