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Artificial Neural Networks-Modern Systems for Safety Control

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Artificial Neural Networks—Modern Systems for Safety Control

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A short review of the applications of artificial neural networks in different fields of industry with a description of their main properties is made. Such systems have specific properties typical for the human brain, which can decide on the superiority of artificial neural networks over standard control systems. Basic types of such networks as well as their principles of operation and successful applications are described. The application of artificial neural networks in safety engineering is discussed with stress on their special properties, which are necessary in safety critical systems.

artificial neural networks safety control

1. INTRODUCTION

Artificial neural networks (ANNs) are systems, which have been extensively studied in the last decade, both by physicists and engineers. This has been so because of ANNs' interesting physical properties and their rich applications. The studies were preceded by the discoveries (honored by seven Nobel Prizes in Physiology) concerning the structure and the activity of a single neural cell of the human brain (neuron) and the whole neural network. Some properties of ANNs (described further) are typical specifically for the human brain. This determines the superiority of ANN-based systems over systems using standard algorithmic methods on conventional computers (Hertz, Krogh, & Palmer, 1995; Nelson & Illingworth, 1994; Patterson, 1996).

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Adaptability is one of the main properties of ANNs. An ANN can learn from examples, which results in its desirable behavior becoming more perfect. It is not necessary to have the knowledge about the process of reaching the solution of the problem presented to the network as is in the case of a standard numerical approach performed by an execution of a program in the computer. The process of learning is based on a set of pairs of input data $\{\mathbf{X}^m\}$ and output data $\{\mathbf{Y}^n\}$ corresponding to input data $\{\mathbf{X}^m\}$. After the process of training, the network can realize the nonlinear mapping f of input data to output data as shown in Figure 1, but the explicit form of f is not known. Moreover, a properly trained ANN is able to find correct outputs also for input signal X^k, which do not belong to the learning set $\{\mathbf{X}^m\}$. This important property is called generalization and is very often performed by the brain.

The ability to handle noisy and incomplete data is another important property of ANNs. Such inputs occur very frequently in reality and constitute a serious problem for standard control systems. Similarly as in the case of the brain, in many cases ANNs are able to react correctly even in the case of perturbed input data.

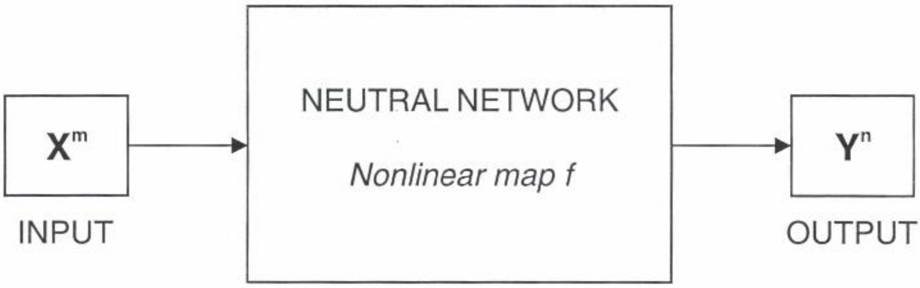

Figure 1. Neural network realizes nonlinear mapping f of input data $\{X^m\}$ to output data $\{Y^m\}$.

ANNs consist of a large number of neurons and each of them individually changes its states in time; therefore, we can say that each of them processes information individually and that the whole network processes information in parallel. This results in the high speed of the work of the network. This property is very important in control systems that work in real time and it is also necessary in other time critical applications.

Resistivity to partial damage is another property of ANNs. In the case of hardware implementations of ANNs, despite partial damage of some elements, the whole network can work correctly, mainly due to the parallel processing of information.

2. SUCCESSFUL APPLICATIONS OF ANNs

In the very extensive scientific literature devoted to ANNs' applications (including specialized international journals like *Neural Networks*, *Neurocomputing*, and *IEEE Transactions on Circuits and Systems*) a large number of successfully working systems has been presented.

Systems for pattern recognition are one of the most common application of ANNs. They were constructed to analyze finger prints (Lynch & Haunt, 1995), radar pictures (Luttrell, 1995), read handwritten letters (Laaksonen & Oja, 1996), analyze the trajectories of particles in accelerators (Kolanoski, 1996), and so forth. Figure 2 shows an example of the recognition of a noised picture of a human face by a neural network (a 3-layer perceptron with 54–15–64 neurons in the layers; Osowski, 1996).

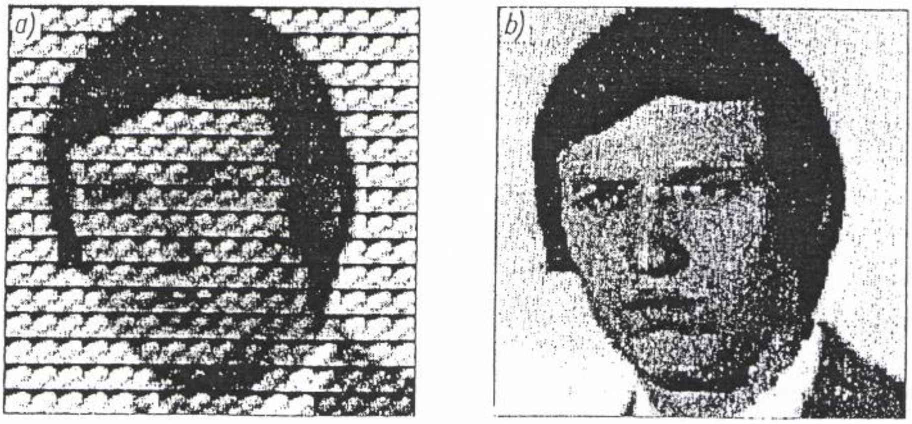

Figure 2. An example of a correct recognition of a noised picture of a human face by an artificial neural network. The figure on the left shows a noised picture of a face, which constitutes input data of the network; the proper picture of this face is one of the patterns stored in the network. The picture on the right shows the output of the network: a clear picture of the same face (Osowski, 1996).

ANNs are very widely used in optimization. They are able to control telecommunication traffic, to classify medical signals (like EEG), to predict economic processes, and so forth (Burgess, 1995; Dumpelmann

& Elger, 1996; Leary, Gallinari, & Didelet, 1996). The Traveling Salesman Problem is a simple but very instructive example showing the solution of an optimization problem. It is very often used for investigating the optimization possibilities of a designed neural network. In this problem the minimal route of a salesman who starts from one port and has to visit each of a given number of randomly located other ports only once, should be found (Kirkpatrick, Gelatt, & Vecci, 1983). An example of the solution of this problem for the case of 400 ports is shown in Figure 3.

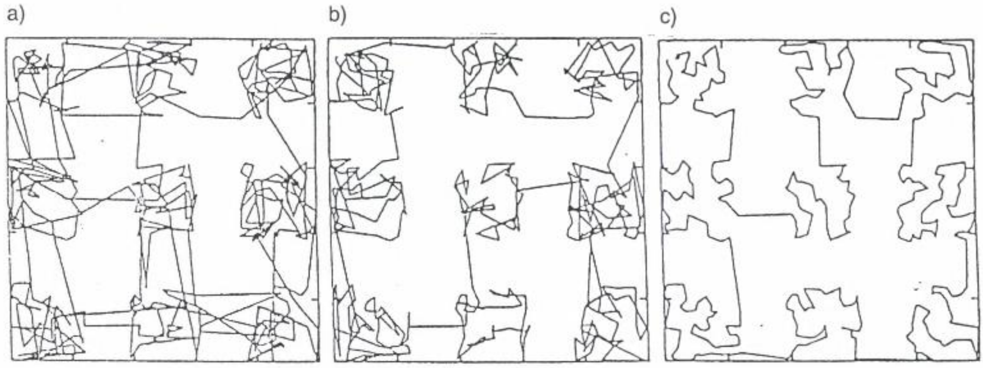

Figure 3. Traveling Salesman Problem solved by a neural network for the case of 400 ports (ports are located in each summit of the line). Some initial states: Figures a and b. Figure c shows the minimal route of the salesman visiting all ports and corresponds to the final state of the network (Müller, Reinhardt, & Strickland, 1995).

In an increasing number of the industrial applications of different kinds of robots ANNs are also used as control systems. In the future, such robots, equipped with a robust ANN, will analyze the spatio-temporal relations in their dynamically changing surroundings and perform very precise actions that can substitute people (e.g., during work in dangerous areas). A number of publications have been devoted to such applications of ANNs; however, the achievement of a level of effectiveness typical for humans is still rather remote (Ritter, Martinez, & Schulten, 1992). Figure 4 presents an example of a mobile robot navigated by ANNs (Leonard & Durrant-Whyte, 1992).

As already mentioned, an ANN is able to perform arbitrary nonlinear mapping of input signals to proper output. Such situations occur in typical technological processes in, for example, chemical industry. There is a number of solutions, in which ANNs control the course of chemical reactions setting parameters at appropriate levels and preventing

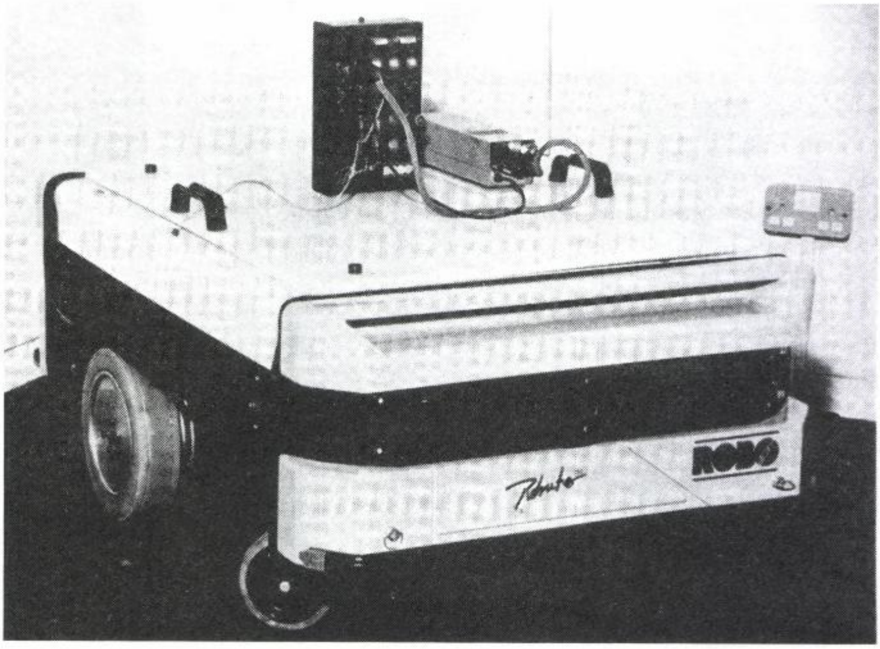

Figure 4. Mobile robot navigated by artificial neural networks (Leonard, J.J., & Durrant-Whyte, H.F., 1992). Reproduced by kind permission of Kluwer Academic Press.

dangerous situations (Molga, 1996). Other applications of ANNs are connected with the recognition of the composition of air or water mixtures. Such systems can analyze the level of pollution in water or air, or control the creation of undesirable chemical reactions. Networks for odor recognition are an example (see, e.g., Lee, Payne, Byunn, & Persaud, 1996).

The aforementioned examples show that the field of applications of ANNs is very wide. On the other hand, up to now research related directly to safety control has been rather limited: Published research has been mainly general (see, e.g., Draghici, 1996; Jarvinen & Karwowski, 1992; Morgan & Austin, 1995). In many cases, existing solutions can be quite easily adapted for use in safety control systems.

3. WHAT IS AN ARTIFICIAL NEURAL NETWORK

In order for ANNs to work in different fields of applications, as mentioned earlier, single neurons have to have different properties and the ANNs have to have different structures and sizes. Here, we present a simple type of an ANN with the main properties characteristic for all ANNs.

An ANN consists of a number of single elements, called neurons, which have rather simple dynamical properties (Figure 5). A neuron can be in one of two states: firing ($S_i = 1$) or rest ($S_i = 0$). The state of the neuron S_i at the time t depends on the signals coming to it from other neurons S_j that were in the earlier states in time $(t - 1)$:

$$S_i(t) = f[\Sigma_j J_{ij} S_j (t - 1)] \tag{1}$$

where f is called activation function and—in the simplest case—is defined as

$$\begin{aligned} f(x) &= 0 \text{ for } x < 0, \\ f(x) &= 1 \text{ for } x \geqslant 0 \end{aligned} \tag{2}$$

and the connections between the i-th neuron and other, j-th, neurons ($j = 1, 2, \dots, N$) are given by a synaptic matrix **[J]**. As we can see, each neuron may be connected with a large number of other neurons (even with all the other neurons in the network). The shape of the synaptic matrix is appropriate for the task that can be realized by the network and is set in the process of the network's learning. Then, during the work of the network, matrix **[J]** remains constant (Figure 6). The change of the state of a single neuron influences the states of all the other neurons, as results from the shape of matrix **[J]** (see Equation 1). This results in a time evolution of the states of the network. Here, the state of the network can be described as an N-bit word, which contains the states of all neurons: For example, the state (100 ... 1) means that $S_1 = 1$, $S_2 = 0$, $S_3 = 0$, ... , $S_N = 1$. During time evolution, the network reaches its final state, which constitutes a desirable solution of the task solved by the network. An example of the time evolution of the network consisting of $N = 8$ neurons is shown on the right hand side of Figure 6. The initial state in the time t_0 changes and after some time steps the network reaches a certain final state in $t = t_m$. From this time the state of the network is constant: Such a case is a possible type of time evolution of the network. It may correspond to the case of recognizing a certain pattern, which belongs to a set of patterns stored in the network earlier, during the process of learning.

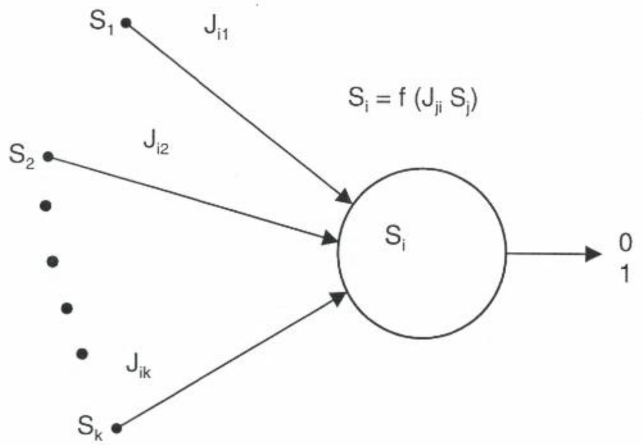

Figure 5. Neuron S_i can have one of two states: 0 (rest) or 1 (firing). This depends on the states of other neurons S_1, S_2, ... , S_k and the connections J_{i1}, J_{i2}, ... , J_{ik} between these neurons and neuron S_i. Activation function f represents the dynamic characteristic of the neuron.

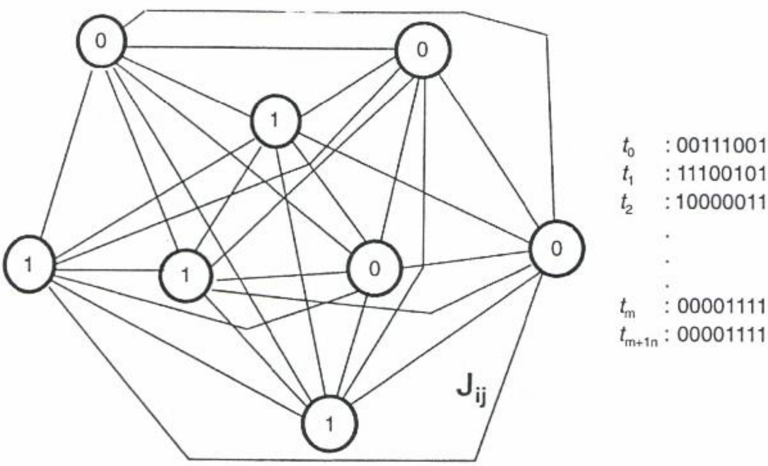

Figure 6. An example of a very simple artificial neural network consisting of N = 8 neurons. Only nonzero connections between neurons J_{ij} are marked. The state of this network is represented by a binary number with 8 digits. The state of the network changes in time, t_0 is the initial state of the network, t_m is the final state of the network. Starting from t_m the state of the network is constant, which may correspond to the recognition of a certain pattern (here: 00001111).

It is worthwhile noticing that the properties of ANNs described earlier (e.g., two-state neurons, large number of neighbors of each neuron, learning ability, time evolution of the network) are characteristic for the human brain, as results from physiological investigations.

As we saw in the previous example, the network has no specific spatial structure, that is, the location of neurons can be arbitrary, provided the shape of matrix [J] is maintained. Such networks are called Hopfield-type networks. It is characteristic that the same neurons receive input signal (cf. Figure 6) and deliver output signal.

There are also many other structures of networks. Among the most important ones are the multilayer Perceptrons shown in Figure 7. In this network, there is an input layer of neurons, which transfer signals to the next layer, called the hidden layer. Then, signals reach the second hidden layer and so on. The last layer is the output layer, which delivers the output signal. Also in this case, the synaptic connections in the network are created in the process of learning. One of the most popular learning procedures for a multilayer perceptron is the back propagation method (for description see, e.g., reference by Patterson, 1996).

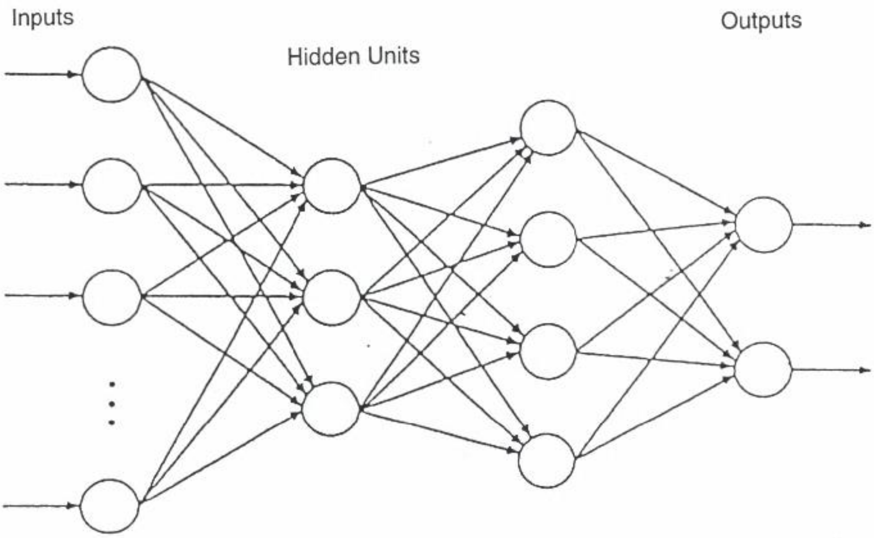

Figure 7. Multilayer Perceptron is a neural network with neurons forming layers: input, some hidden layers, and an output layer.

Cellular artificial networks are an important type of ANNs. In this type of network, locations of neurons correspond to the location of the elements in the matrix (see Figure 8) and each neuron (except the ones at the edges of the matrix) has the same type of connection with its neighbors, the so-called cloning template (Chua & Yang, 1988). In this case, as in the case of the Hopfield-type networks (Hertz et al., 1995;

Patterson, 1996), the same neurons receive input signals and deliver output signals. The applications of such networks are very interesting: They can detect the motion of objects (Chua & Yang, 1988), detect objects of a specified shape (Zarandy, Werblin, Roska, & Chua, 1994), remove noise from patterns (Yang, Yang, & Yang, 1994), and so forth. Figure 9 is an example of the work of a cellular neural network designed for detecting motion (Kacprzyk & Ślot, 1995). Figure 9a shows the initial binary picture presented to the network, Figure 9b shows the next picture, in which some objects are shifted in comparison to those in Figure 9a, and Figure 9c shows the output of the network: The moving objects are extracted from the picture.

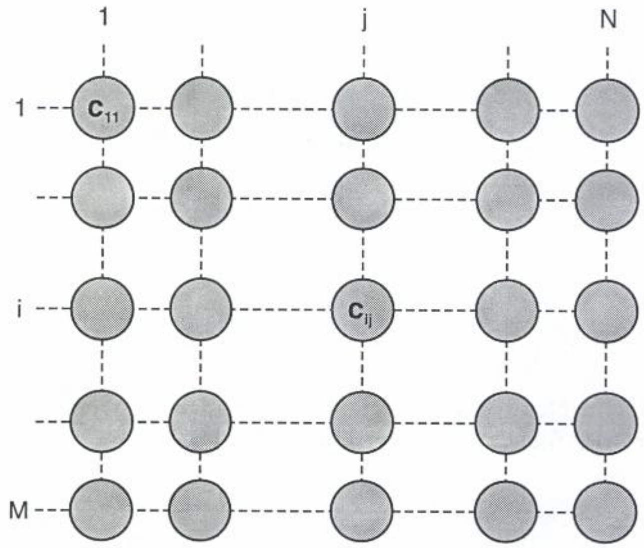

Figure 8. Cellular neural network of the size M × N. The location of each neuron is described by indices ij.

We are not describing other important types of ANNs like Kohonen networks, ARTmap network, and so forth. There are also networks with continuous time, in which time evolution is described by a set of coupled differential equations, not by coupled maps, like in the case of discrete time networks presented earlier (see Equation 1). Moreover, in some applications, neurons with more than two stable states can be used (e.g., continuous states). A review of the different types of networks is presented in basic books on ANNs (see, e.g., Muller, Reinhardt, & Strickland, 1995; Patterson, 1996).

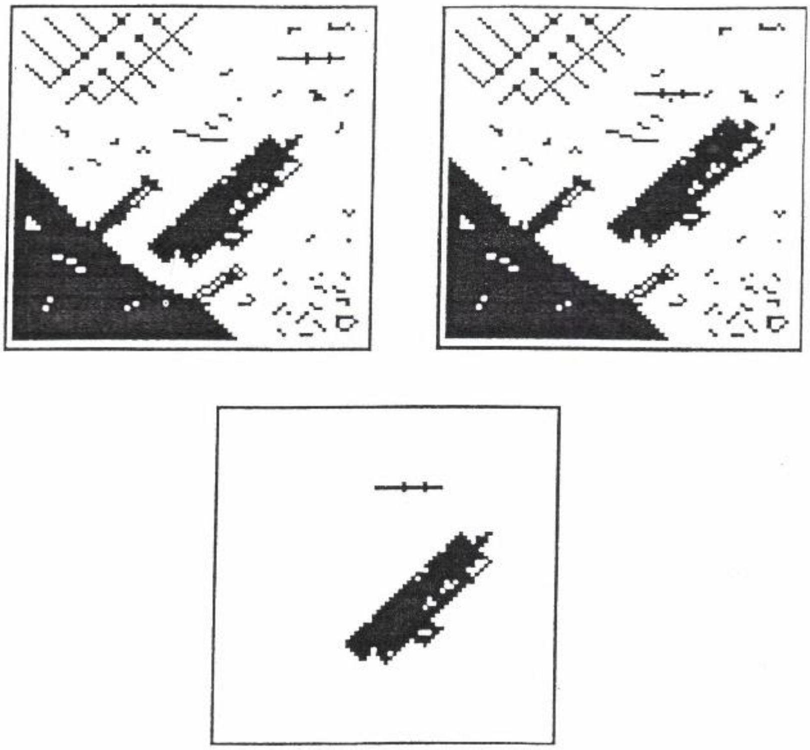

Figure 9. Cellular neural network can detect moving objects. The figure on the left shows a certain picture in time t, the figure on the right shows the same picture in later time $t + 1$, the picture at the bottom shows moving objects extracted by the network (Kacprzyk & Ślot, 1995).

There are two main types of implementations of ANNs. One is a computer simulation of ANNs, sometimes with computers with special architecture, which accelerates the operation of the network. In this case, it is relatively easy to modify the structure and the internal parameters of the network. The other type of implementation of ANNs is the realization of an ANN as an electronic circuit consisting of discrete elements or as an integrated electronic circuit. The latter type of implementation is much more expensive than the former. For instance, designing a separate microchip containing an ANN is a complex task requiring high technology laboratories. Moreover, in such a case no changes of the ANN structure are possible. Therefore, this type of implementation is rather used in the case of ANNs that are control elements produced in large scale industrial manufacturing.

4. REQUIREMENTS FOR ANNs IN SAFETY ENGINEERING

There are no universal or reliable techniques that allow designing ANNs for safety engineering purposes, however, some useful steps have been taken (Draghici, 1996; Jarvinen & Karwowski, 1992; Kuivanen, 1995; Morgan & Austin, 1995). In this process, general requirements typical for safety robotics can be adapted (Kuivanen, 1995). Such a system must comply with the requirements of the EN and ISO standards (ISO 9001:1994; International Organization for Standardization, 1994).

Safety requirements depend on the type of implementation of an ANN. In all types of implementations, special attention must be paid to desirable safety critical properties. In the process of designing an ANN for safety control systems, some specific stages can be distinguished (Morgan & Austin, 1995).

System specification is a stage at which a description of what the ANN should do is made. It defines the type, internal structure, and the number of neurons in the network. A set of dangerous situations (and the ANN states referring to them) should be chosen at this stage, too. Next, a proper learning algorithm, in which the possibility of undesirable network reaction is minimalized, should be constructed.

Implementation. In the case of a computer implementation of an ANN, it is necessary to construct a numerical algorithm simulating its operation with a high level of reliability. In standard programs prepared by professionals, there still are errors: approximately one per each 300 lines. Therefore, special procedures of preparing numerical programs (widely used, e.g., in aircraft computers) should be used for safety applications (Rodd, 1995). The process of testing a program that simulates an ANN should reveal all errors that would lead to a dangerous reaction of an ANN (e.g., in the process of generalization). In the case of hardware implementation, special attention should be paid to the quality of the elements used in the circuit and to manufacturing. The system should be able to tolerate a certain amount of damage of discrete elements. This can be achieved by a proper structure of the ANN and its parallel processing of information.

Verification and validation is a process in which the correct operation of the system is controlled. After ANNs' learning with the training set of data, their operation is controlled using a separate set of test data. In the behavior of the whole ANN system, unexpected and potentially dangerous situations should not occur, or they should be eliminated by a correct setting of adjustable parameters.

Reliability of the system depends on many factors: the structure of the system, the size of the network, the reliability of discrete elements, and so forth. For instance, a typical level of reliability accepted in aircraft engineering is obtained if the probability of occurrence of critical damage is less than 10^{-9} per hour of work (Rodd, 1995). A similar level of reliability of ANNs should be achieved in control systems. There are many methods of increasing the reliability of complex systems. In particular, at the stage of designing the structure of an ANN, redundant neurons can be added to the network in order to obtain a more reliable system (Johnson, Picto, & Hallam, 1993; Morgan & Austin, 1995).

There are also some specific problems that are immanently connected with applications of ANNs. As mentioned earlier, in the process of designing an ANN, the explicit algorithm of its operation is not known. Therefore, we do not known all the possible responses of an ANN to coming input signals. A proper process of learning should eliminate undesirable network reactions, however, the probability of a wrong reaction of an ANN is not zero.

Another problem of ANN applications as control systems is connected with their satisfactory speed of processing information. The process of analyzing a large amount of information coming from TV sensors (e.g., in the case of observing a robot's surroundings) requires ANNs with a rather high number of neurons. Despite the parallel processing of information in the network, time necessary to generate a proper output signal can be considerable, and sometimes too long for the work of an ANN control system as a real-time element. Such problems are common in the rapidly expanding area of virtual reality systems (Lin & Kuo, 1997). Of course, satisfactory speed of ANNs elements can be achieved by using a computer with high speed processors or, in the case of a hardware implementation of the network, by using electronic elements with a high speed of commutations.

5. PROSPECTS OF APPLICATIONS OF ANNs IN SAFETY CONTROL SYSTEMS

A number of existing applications of ANNs can be rather easily adapted to safety control. The application of an odor recognition system as a system for detecting dangerous levels of different compounds emitted in industrial manufacturing processes is one such possibility. An example is schematically shown in Figure 10 (Corcoran & Lowery, 1995). A set of sensors sensitive to the presence of different compounds (e.g., changing their resistivity) is an important part of a system like that. It makes analyzing the mixture of different compounds in the air possible.

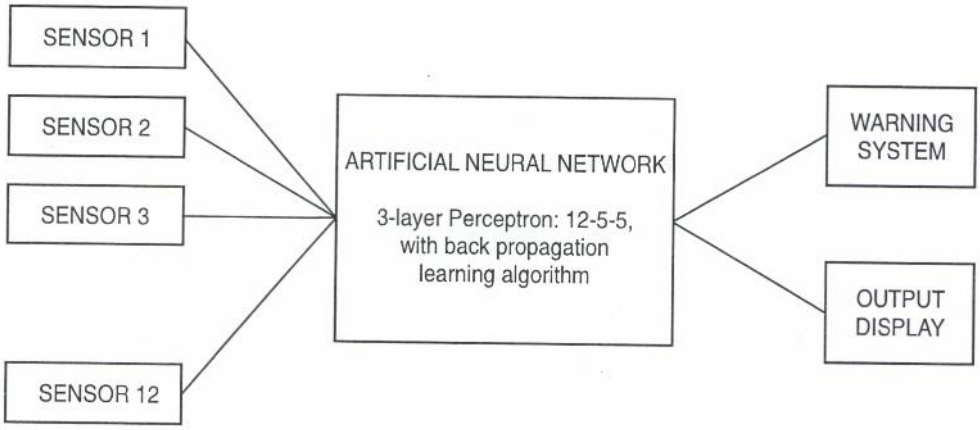

Figure 10. Schematic view of an Odour Sensing System based on a 3-layer Perceptron and learned with a back propagation algorithm (Corcoran & Lowery, 1995).

By using specific electrodes as sensors it is also possible to detect the level of dangerous compounds in water (Manvarig, 1995).

Particularly interesting applications of ANNs in safety control can be connected with robots. ANNs can detect dangerous situations at robotized work stands. The currently used systems controlling safety at work stands with stationary robots (based, e.g., on light curtains) very frequently stop the robot in situations that are not, in principle, dangerous. This results in losses in the manufacturing process. An ANN control system can intelligently analyze the surroundings of a robot and react only in really dangerous situations. For instance, such a control system can detect the size and velocity of an object that is approaching a robot and that might collide with it, and stops it only if this object is large enough and is moving with a certain velocity (e.g., typical for a human). An example of such a system is shown in Figure 11 (Kosiński, 1996).

Another interesting application of an ANN is its use as a navigation system in a mobile robot. Such robots would substitute the work of men in dangerous zones (e.g., with a high level of radiation) or in areas with

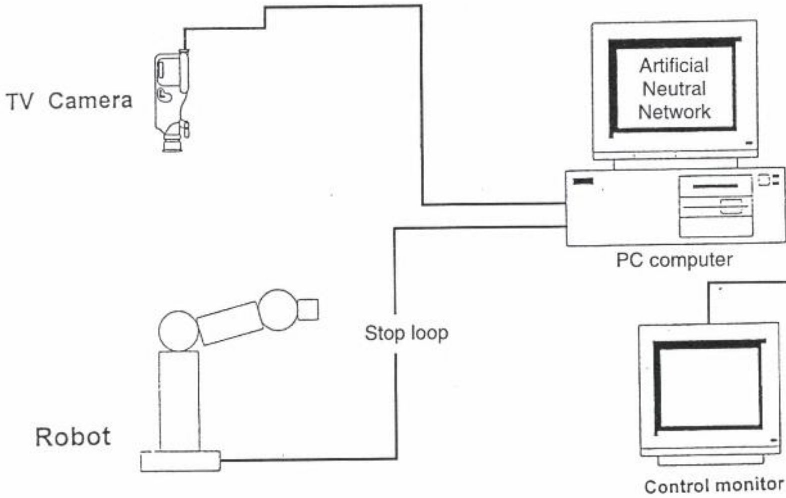

Figure 11. Schematic view of a Control System for detecting dangerous situations at a work stand with a robot, based on an artificial neural network (Kosiński, 1996).

difficult access. There is extensive literature devoted to such applications. However, presently, the level of control of robot motion performed by ANN systems is still very distant from the level characteristic for the human brain. Problems appearing in such control are really extremely complex. In a mobile robot's surroundings there can be objects of different and changing size, moving with different and changing velocities. Moreover, the conditions of vision can also change, sometimes abruptly, and so forth. Analysis of this large stream of information should result in proper commands to the engines and brakes of the robot. Such problems are easily solved by a human, for example, when driving in heavy traffic. By comparison, a contemporary ANN system can drive a car on a rather empty highway with a very limited number of potentially dangerous situations, like passing approaching cars, simple overtaking cars moving with constant velocity, and so forth (Kaiser & Wallner, 1996).

In view of the advantages of ANNs and the very significant development in the field of theoretical and practical treatment of ANNs, we can expect that in the nearest future the number of applications of ANNs in the systems used in safety control will significantly increase.

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