SECOND EDITION

The Industrial Electronics Handbook

INTELLIGENT SYSTEMS

Edited by
Bogdan M. Wilamowski
J. David Irwin

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Preface

The field of industrial electronics covers a plethora of problems that must be solved in industrial practice. Electronic systems control many processes that begin with the control of relatively simple devices like electric motors, through more complicated devices such as robots, to the control of entire fabrication processes. An industrial electronics engineer deals with many physical phenomena as well as the sensors that are used to measure them. Thus, the knowledge required by this type of engineer is not only traditional electronics but also specialized electronics, for example, that required for high-power applications. The importance of electronic circuits extends well beyond their use as a final product in that they are also important building blocks in large systems, and thus the industrial electronics engineer must also possess knowledge of the areas of control and mechatronics. Since most fabrication processes are relatively complex, there is an inherent requirement for the use of communication systems that not only link the various elements of the industrial process but are also tailor-made for the specific industrial environment. Finally, the efficient control and supervision of factories require the application of intelligent systems in a hierarchical structure to address the needs of all components employed in the production process. This need is accomplished through the use of intelligent systems such as neural networks, fuzzy systems, and evolutionary methods. The Industrial Electronics Handbook addresses all these issues and does so in five books outlined as follows:

1. *Fundamentals of Industrial Electronics*
2. *Power Electronics and Motor Drives*
3. *Control and Mechatronics*
4. *Industrial Communication Systems*
5. *Intelligent Systems*

The editors have gone to great lengths to ensure that this handbook is as current and up to date as possible. Thus, this book closely follows the current research and trends in applications that can be found in *IEEE Transactions on Industrial Electronics*. This journal is not only one of the largest engineering publications of its type in the world, but also one of the most respected. In all technical categories in which this journal is evaluated, it is ranked either number 1 or number 2 in the world. As a result, we believe that this handbook, which is written by the world's leading researchers in the field, presents the global trends in the ubiquitous area commonly known as industrial electronics.

An interesting phenomenon that has accompanied the progression of our civilization is the systematic replacement of humans by machines. As far back as 200 years ago, human labor was replaced first by steam machines and later by electrical machines. Then approximately 20 years ago, clerical and secretarial jobs were largely replaced by personal computers. Technology has now reached the point where intelligent systems are replacing human intelligence in decision-making processes as well as aiding in the solution of very complex problems. In many cases, intelligent systems are already outperforming human activities. The field of computational intelligence has taken several directions. Artificial neural networks are not only capable of learning how to classify patterns, for example, images or sequences of

events, but they can also effectively model complex nonlinear systems. Their ability to classify sequences of events is probably more popular in industrial applications where there is an inherent need to model nonlinear system behavior—as an example, measuring the system parameters that are easily obtainable and using a neural network to evaluate parameters that are difficult to measure but essential for system control. Fuzzy systems have a similar application. Their main advantage is their simplicity and ease of implementation. Various aspects of neural networks and fuzzy systems are covered in Parts II and III. Part IV is devoted to system optimization, where several new techniques including evolutionary methods, swarm, and ant colony optimizations are covered. Part V is devoted to several applications that deal with methods of computational intelligence.

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Editors

Bogdan M. Wilamowski received his MS in computer engineering in 1966, his PhD in neural computing in 1970, and Dr. habil. in integrated circuit design in 1977. He received the title of full professor from the president of Poland in 1987. He was the director of the Institute of Electronics (1979–1981) and the chair of the solid state electronics department (1987–1989) at the Technical University of Gdansk, Poland. He was a professor at the University of Wyoming, Laramie, from 1989 to 2000. From 2000 to 2003, he served as an associate director at the Microelectronics Research and Telecommunication Institute, University of Idaho, Moscow, and as a professor in the electrical and computer engineering department and in the computer science department at the same university. Currently, he is the director of ANMSTC—Alabama Nano/Micro Science and Technology Center, Auburn, and an alumna professor in the electrical and computer engineering department at Auburn University, Alabama. Dr. Wilamowski was with the Communication Institute at Tohoku University, Japan (1968–1970), and spent one year at the Semiconductor Research Institute, Sendai, Japan, as a JSPS fellow (1975–1976). He was also a visiting scholar at Auburn University (1981–1982 and 1995–1996) and a visiting professor at the University of Arizona, Tucson (1982–1984). He is the author of 4 textbooks, more than 300 refereed publications, and has 27 patents. He was the principal professor for about 130 graduate students. His main areas of interest include semiconductor devices and sensors, mixed signal and analog signal processing, and computational intelligence.

Dr. Wilamowski was the vice president of the IEEE Computational Intelligence Society (2000–2004) and the president of the IEEE Industrial Electronics Society (2004–2005). He served as an associate editor of *IEEE Transactions on Neural Networks*, *IEEE Transactions on Education*, *IEEE Transactions on Industrial Electronics*, the *Journal of Intelligent and Fuzzy Systems*, the *Journal of Computing*, and the *International Journal of Circuit Systems and IES Newsletter*. He is currently serving as the editor in chief of *IEEE Transactions on Industrial Electronics*.

Professor Wilamowski is an IEEE fellow and an honorary member of the Hungarian Academy of Science. In 2008, he was awarded the Commander Cross of the Order of Merit of the Republic of Poland for outstanding service in the proliferation of international scientific collaborations and for achievements in the areas of microelectronics and computer science by the president of Poland.

J. David Irwin received his BEE from Auburn University, Alabama, in 1961, and his MS and PhD from the University of Tennessee, Knoxville, in 1962 and 1967, respectively.

In 1967, he joined Bell Telephone Laboratories, Inc., Holmdel, New Jersey, as a member of the technical staff and was made a supervisor in 1968. He then joined Auburn University in 1969 as an assistant professor of electrical engineering. He was made an associate professor in 1972, associate professor and head of department in 1973, and professor and head in 1976. He served as head of the Department of Electrical and Computer Engineering from 1973 to 2009. In 1993, he was named Earle C. Williams Eminent Scholar and Head. From 1982 to 1984, he was also head of the Department of Computer Science and Engineering. He is currently the Earle C. Williams Eminent Scholar in Electrical and Computer Engineering at Auburn.

Dr. Irwin has served the Institute of Electrical and Electronic Engineers, Inc. (IEEE) Computer Society as a member of the Education Committee and as education editor of *Computer*. He has served as chairman of the Southeastern Association of Electrical Engineering Department Heads and the National Association of Electrical Engineering Department Heads and is past president of both the IEEE Industrial Electronics Society and the IEEE Education Society. He is a life member of the IEEE Industrial Electronics Society AdCom and has served as a member of the Oceanic Engineering Society AdCom. He served for two years as editor of *IEEE Transactions on Industrial Electronics*. He has served on the Executive Committee of the Southeastern Center for Electrical Engineering Education, Inc., and was president of the organization in 1983–1984. He has served as an IEEE Adhoc Visitor for ABET Accreditation teams. He has also served as a member of the IEEE Educational Activities Board, and was the accreditation coordinator for IEEE in 1989. He has served as a member of numerous IEEE committees, including the Lamme Medal Award Committee, the Fellow Committee, the Nominations and Appointments Committee, and the Admission and Advancement Committee. He has served as a member of the board of directors of IEEE Press. He has also served as a member of the Secretary of the Army's Advisory Panel for ROTC Affairs, as a nominations chairman for the National Electrical Engineering Department Heads Association, and as a member of the IEEE Education Society's McGraw-Hill/Jacob Millman Award Committee. He has also served as chair of the IEEE Undergraduate and Graduate Teaching Award Committee. He is a member of the board of governors and past president of Eta Kappa Nu, the ECE Honor Society. He has been and continues to be involved in the management of several international conferences sponsored by the IEEE Industrial Electronics Society, and served as general cochair for IECON'05.

Dr. Irwin is the author and coauthor of numerous publications, papers, patent applications, and presentations, including *Basic Engineering Circuit Analysis*, 9th edition, published by John Wiley & Sons, which is one among his 16 textbooks. His textbooks, which span a wide spectrum of engineering subjects, have been published by Macmillan Publishing Company, Prentice Hall Book Company, John Wiley & Sons Book Company, and IEEE Press. He is also the editor in chief of a large handbook published by CRC Press, and is the series editor for Industrial Electronics Handbook for CRC Press.

Dr. Irwin is a fellow of the American Association for the Advancement of Science, the American Society for Engineering Education, and the Institute of Electrical and Electronic Engineers. He received an IEEE Centennial Medal in 1984, and was awarded the Bliss Medal by the Society of American Military Engineers in 1985. He received the IEEE Industrial Electronics Society's Anthony J. Hornfeck Outstanding Service Award in 1986, and was named IEEE Region III (U.S. Southeastern Region) Outstanding Engineering Educator in 1989. In 1991, he received a Meritorious Service Citation from the IEEE Educational Activities Board, the 1991 Eugene Mittelmann Achievement Award from the IEEE Industrial Electronics Society, and the 1991 Achievement Award from the IEEE Education Society. In 1992, he was named a Distinguished Auburn Engineer. In 1993, he received the IEEE Education Society's McGraw-Hill/Jacob Millman Award, and in 1998 he was the recipient of the

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I

Introductions

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1

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Ryszard Tadeusiewicz
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1.1 Introduction

Numerous intelligent systems, described and discussed in the subsequent chapters, are based on different approaches to machine intelligence problems. The authors of these chapters show the necessity of using various methods for building intelligent systems. Almost every particular problem needs an individual solution; thus, we can study many different intelligent systems reported in the literature. This chapter is a kind of introduction to particular systems and different approaches presented in the book. The role of this chapter is to provide the reader with a bird's eye view of the area of intelligent systems. Before we explain what intelligent systems are and why it is worth to study and use them, it is necessary to comment on one problem connected with the terminology.

The problems of equipping artificial systems with intelligent abilities are, in fact, unique. We always want to achieve a general goal, which is a better operation of the intelligent system than one, which can be accomplished by a system without intelligent components. There are many ways to accomplish this goal and, therefore, we have many kinds of artificial intelligent (AI) systems. In general, it should be stressed that there are two distinctive groups of researches working in these areas: the AI community and the computational intelligence community. The goal of both groups is the same: the need for artificial systems powered by intelligence. However, different methods are employed to achieve this goal by different communities.

AI [LS04] researchers focus on the imitation of human thinking methods, discovered by psychology, sometimes philosophy and so-called cognitive sciences. The main achievements of AI are traditionally rule-based systems in which computers follow known methods of human thinking and try to achieve similar results as human. Mentioned below, and described in detail in a separate chapter, expert systems are good examples of this AI approach.

Computational intelligence [PM98] researchers focus on the modeling of natural systems, which can be considered as intelligent ones. The human brain is definitely the source of intelligence; therefore, this area of research focuses first on neural networks, very simplified but efficient in practical application models of small parts of the biological brain. There are also other natural processes, which can be used (when appropriately modeled) as a source of ideas for successful AI systems. We mention, e.g., swarm intelligence models, evolutionary computations, and fuzzy systems.

The differentiation between AI and computational intelligence (also known as soft computing [CM05]) is important for researchers and should be obeyed in scientific papers for its proper classification. However, from the point of view of applications in intelligent systems, it can be disregarded. Therefore, in the following sections, we will simply use only one name (artificial intelligence) comprising both artificial intelligence and computational intelligence methods. For more precise differentiations and for tracing bridges between both approaches mentioned, the reader is referred to the book [RT08].

The term "artificial intelligence" (AI) is used in a way similar to terms such as mechanics or electronics but the area of research and applications that belong to AI are not as precisely defined as the other areas of computer science. The most popular definitions of AI are always related to the human mind and its emerging property: natural intelligence. At times it was fashionable to discuss the general definition of AI as follows: Is AI at all possible or not? Almost everybody knows Turing's answer to this question [T48], known as "Turing test," where a human judge must recognize if his unknown-to-him partner in discussion is an intelligent (human) person or not. Many also know Searle's response to the question, his "Chinese room" model [S80]. For more information about these contradictions, the reader is referred to the literature listed at the end of this chapter (a small bibliography of AI), as well as to a more comprehensive discussion of this problem in thousands of web pages on the Internet. From our point of view, it is sufficient to conclude that the discussion between supporters of "strong AI" and their opponents is still open—with all holding their opinions.

For the readers of this volume, the results of these discussions are not that important since regardless of the results of the philosophical roll outs—"intelligent" systems were built in the past, are used contemporarily, and will be constructed in the future. It is because intelligent systems are very useful for all, irrespective of their belief in "strong AI" or not. Therefore in this chapter, we do not try to answer the fundamental question about the existence of the mind in the machine. We just present some useful methods and try to explain how and when they can be used. This detailed knowledge will be presented in the next few sections and chapters. At the beginning, let us consider neural networks.

1.2 Historical Perspective

This chapter is not meant to be a history of AI because the users are interested in exploiting mature systems, algorithms, or technologies, regardless of long and difficult ways of systematic development of particular methods as well as serendipities that were important milestones in AI's development. Nevertheless, it is good to know that the oldest systems, solving many problems by means of AI methods, were neural networks. This very clever and user-friendly technology is based on the modeling of small parts of real neural system (e.g., small pieces of the brain cortex) that are able to solve practical problems by means of learning. The neural network theory, architecture, learning, and methods of application will be discussed in detail in other chapters; therefore, here we only provide a general outline.

One was mentioned above: neural networks are the oldest AI technology and it is still the leading technology if one counts number of practical applications. When the first computers were still large and clumsy, the neurocomputing theorists, Warren Sturgis McCulloch and Walter Pitts, published "A logical calculus of the ideas immanent in nervous activity" [MP43], thus laying foundations for the field of artificial neural networks. This paper is considered as the one that started the entire AI area. Many books

written earlier and quoted sometimes as heralds of AI were only theoretical speculations. In contrast, the paper just quoted was the first constructive proposition on how to build AI on the basis of mimicking brain structures. It was a fascinating and breakthrough idea in the area of computer science.

During many years of development, neural networks became the first working AI systems (Perceptron by Frank Rosenblatt, 1957), which was underestimated and it lost "steam" because of the (in)famous book by Marvin Minski [MP72], but returned triumphantly as an efficient tool for practical problem solving with David Rumelhart's discovery of backpropagation learning method [RM86]. Since the mid-1980s the power and importance of neural networks permanently increased, reaching now a definitely leading position in all AI applications. However, its position is somehow weakened because of the increase in popularity and importance of other methods belonging to the so-called soft computing. But if one has a problem and needs to solve it fast and efficiently—one can still choose neural networks as a tool that is easy to use, with lots of good software available.

The above comments are the reason we pointed out neural networks technology in the title of this chapter with the descriptive qualification "first." From the historical point of view, neural network was the first AI tool. From the practical viewpoint, it should be used as the first tool, when practical problems need to be solved. It is great chance that the neural network tool you use turns out good enough and you do not need any more. Let me give you advice, taken from long years of experience in solving hundreds of problems with neural networks applications. There are several types of neural networks elaborated on and discovered by hundreds of researchers. But the most simple and yet successful tool in most problems is the network called MLP (multilayer perceptron [H98]). If one knows exactly the categories and their exemplars, one may use this network with a learning rule such as the conjugate gradient method. If, on the other hand, one does not know what one is expecting to find in the data because no prior knowledge about the data exists, one may use another popular type of neural network, namely, the SOM (self-organizing map), also known as Kohonen network [K95], which can learn without the teacher. If one has an optimization problem and needs to find the best solution in a complex situation, one can use the recursive network, known as the Hopfield network [H82]. Experts and practitioners can of course use also other types of neural networks, described in hundreds of books and papers but it will be a kind of intellectual adventure, like off-road expedition. Our advice is like signposts pointing toward highways; highways are boring but lead straight to the destination. If one must solve a practical problem, often there is no time for adventures.

1.3 Human Knowledge Inside the Machine—Expert Systems

Neural networks discussed in the previous section, of which detailed descriptions can be found in the following chapter, are very useful and are effective tools for building intelligent systems but they have one troublesome limitation. There is a huge gap between the knowledge encoded in the neural network structure during the learning process, and easy for human understanding knowledge presented in any intelligible form (mainly based on symbolic forms and natural language statements). It is very difficult to use knowledge that is captured by the neural network during its learning process, although sometimes this knowledge is the most valuable part of the whole system (e.g., in forecasting systems, where neural networks sometimes are—after learning—a very successful tool, but nobody knows how and why).

The above-mentioned gap is also present when going in the opposite way, e.g., when we need to add man's knowledge to the AI system. Sometimes (and, in fact, very often) we need to have in an automatic intelligent system some part of this knowledge embedded, which can be obtained from the human expert. We need to insert this knowledge into an automatic intelligent system because it is often easier and cheaper to use a computer program instead of constantly asking humans for expert opinion or advice.

Such design with computer-based shell and human knowledge inside it is known as an expert system [GR89]. Such a system can answer the questions not only searching inside internal knowledge representation but can also use methods of automatic reasoning for automatic deriving of conclusions needed by

the user. The expert system can be very helpful for many purposes, combining the knowledge elements extracted from both sources of information: explicit elements of human expert wisdom collected in the form of the knowledge base in computer memory, and elements of user knowledge hidden in the system and emerged by means of automatic reasoning methods after questioning the system.

The main difference between the expert systems and neural networks is based on the source and form of knowledge, which is used in these two AI tools for practical problem solving. In neural networks, the knowledge is hidden and has no readable form but can be collected automatically on the base of examples forming the learning data set. Results given by neural networks can be true and very useful but never comprehensible to users, and therefore must be treated with caution. On the other hand, in the expert system, everything is transparent and intelligible (most of such systems can provide explanations of how and why the particular answer was derived) but the knowledge used by the system must be collected by humans (experts themselves or knowledge engineers who interview experts), properly formed (knowledge representation is a serious problem), and input into the system's knowledge base. Moreover, the methods of automatic reasoning and inference rules must be constructed by the system designer and must be explicit to be built into the system's structure. It is always difficult to do so and sometimes it is the source of limitations during the system's development and exploitation.

1.4 Various Approaches to Intelligent Systems

There are various approaches to intelligent systems but fundamental difference is located in the following distinction: the methods under consideration can be described as symbolic versus holistic ones.

In general, the domain of AI (very wide and presented in this chapter only as a small piece) can be divided or classified using many criteria. One of the most important divisions of the whole area can be based on the difference between the symbolic and holistic (pure numerical) approach. This discriminates all AI methods but can be shown and discussed on the basis of only two technologies presented here—neural networks and expert systems. Neural networks are technology definitely dedicated toward quantitative (numerical) calculations. Signals on input, output, and, most importantly, every element inside the neural network, are in the form of numbers even if their interpretation is of a qualitative type. It means that we must convert qualitative information into quantitative representation in the network. This problem is out of the scope of this chapter; therefore, we only mention a popular way of such a conversion, called "one of *N*." The merit of this type of data representation is based on spreading one qualitative input to *N* neurons in the input layer, where *N* is a number of distinguishable quantitative values, which can be observed in a considered data element. For example, if a qualitative value under consideration is "country of origin" and if there are four possible countries (let us say the United States, Poland, Russia, Germany) we must use for representation of this data four neurons with all signals equaling zero, except one input, corresponding to the selected value in input data, where the signal is equal 1. In this representation, 0,1,0,0 means Poland, etc. The identical method is used for the representation of output signals in neural networks performing a classification task. Output from such a network is in theory singular, because we expect only one answer: label of the class to which a classified object belongs given the input of the network at this moment. But because the label of the class is not a quantitative value—we must use in the output layer of the network as many neurons as there are classes—and the classification process will be assessed as successful when an output neuron attributed to the proper class label will produce a signal much stronger than other output neurons.

Returning to the general categorization of AI methods: qualitative versus quantitative we point out expert systems as a typical tool for the processing of qualitative (symbolic) data. The source of power in every expert system is its knowledge base, which is constructed from elements of knowledge obtained

from human experts. Such elements of knowledge are different from the merit point of view because the expert system can be designed for solving different problems. Also, the internal representation of the human knowledge in a particular computer system can be different, but always in its symbolic form (sometimes even linguistic [natural language sentences]).

The methods of symbolic manipulations were always very attractive for AI researchers because the introspective view of human thinking process is usually registered in a symbolic form (so-called internal speech). Thus, in our awareness, almost every active cognitive process is based on symbol manipulations. Also, from the psychological point of view, the nature of activity of the human mind is defined as analytical-synthetical. What is especially emphasized is the connection between thinking and speaking (language), as the development of either of these abilities is believed to be impossible to exist in separation one from another.

Therefore "founding fathers" of AI in their early works massively used symbolic manipulations as tools for AI problem solving. The well-known example of this stream of works was the system named GPS (General Problem Solver) created in 1957 by Herbert Simon and Allen Newell [NS59]. It was a famous example, but we stress that a lot of AI systems based on symbolic manipulations and applying diverse approaches have been described in the literature. They were dedicated to automatic proving of mathematical theorems, playing a variety of games, solving well-formalized problems (e.g., Towers of Hanoi problem), planning of robot activities in artificial environments ("blocks world"), and many others. Also, early computer languages designed for AI purposes (e.g., LISP) were symbolic.

The differentiation between symbolic manipulations (as in expert systems) and holistic evaluation based on numerical data (like in neural networks) is observable in AI technology. It must be taken into account by every person who strives for the enhancement of designed or used electronic systems powering them by AI supplements.

We note one more surprising circumstance of the above discussed contradiction. Our introspection suggests a kind of internal symbolic process, which is accompanied with every metal process inside the human brain. At the same time, neural networks that are models of the human brain are not able to use symbolic manipulation at all!

AI methods and tools are used for many purposes but one of the most important areas where AI algorithms are used with good results is for problems connected with pattern recognition. The need of data classification is very popular because if we can classify the data, we can also better understand the information hidden in the data streams and thus can pursue knowledge extraction from the information.

In fact, to be used in AI automatic classification methods, we must take into account two types of problems and two groups of methods used for problem solution.

1.5 Pattern Recognition and Classifications

The first one is a classical pattern recognition problem with many typical methods used for its solving. At the start of all such methods, we have a collection of data and—as a presumption—a set of precisely defined classes. We need a method (formal algorithm or simulated device like neural network) for automatic decision making as to which class a particular data point belongs. The problem under consideration is important from a practical point of view because such classification-based model of data mining is one of the most effective tools for discovering the order and internal structure hidden in the data. This problem is also interesting from the scientific point of view and often difficult to solve because in most pattern recognition tasks, we do not have any prior knowledge about classification rules. The relationship between data elements and the classes to which these data should be classified is given only in the form of collection of properly classified examples. Therefore, all pattern recognition problems are examples of inductive reasoning tasks and need some machine learning approach that is both interesting and difficult [TK09].

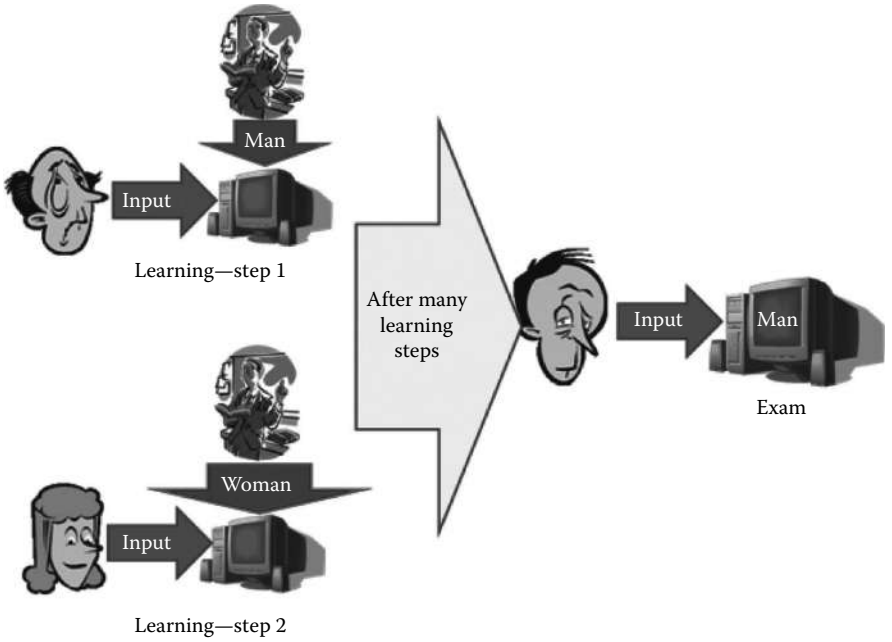

FIGURE 1.1 Pattern recognition problem with supervised learning used.

Machine learning methods can be divided into two general parts. The first part is based on supervised learning while the second part is related to unsupervised learning, also called self-learning or learning without teacher.

An example of supervised learning is presented in Figure 1.1. The learning system (represented by computer with learning algorithm inside) receives information about some object (e.g., man's face). The information about the object is introduced through the system input when the teacher guiding the supervised learning process prompts proper name of the class, to which this object should be numbered among. The proper name of the class is "Man" and this information is memorized in the system. Next another object is shown to the system, and for every object, teacher gives additional information, to which class this object belongs. After many learning steps, system is ready for exam and then a new object (never seen before) is presented. Using the knowledge completed during the learning process, the system can recognize unknown objects (e.g., a man).

In real situations, special database (named learning set) is used instead of human teacher. In such database, we have examples of input data as well as proper output information (results of correct recognition). Nevertheless, the general scheme of supervised learning, shown in Figure 1.2, is fulfilled also in this situation.

Methods used in AI for pattern recognition vary from simple ones, based on naïve geometrical intuitions used to split data description space (or data features space) into parts belonging to different classes (e.g., *k*-nearest neighbor algorithm), through methods in which the computer must approximate borders between regions of data description space belonging to particular classes (e.g., discriminant function methods or SVM algorithms), up to syntactic methods based on structure or linguistics, used for description of classified data [DH01].

A second group of problems considered in AI and related to the data classification tasks is cluster analysis [AB84]. The characteristics of these problems are symmetrical (or dual) to the above-mentioned pattern recognition problems. Whereas in pattern recognition we have predefined classes and need a method for establishing membership for every particular data point into one of such classes, in cluster analysis, we only have the data and we must discover how many groups are in the data. There are many

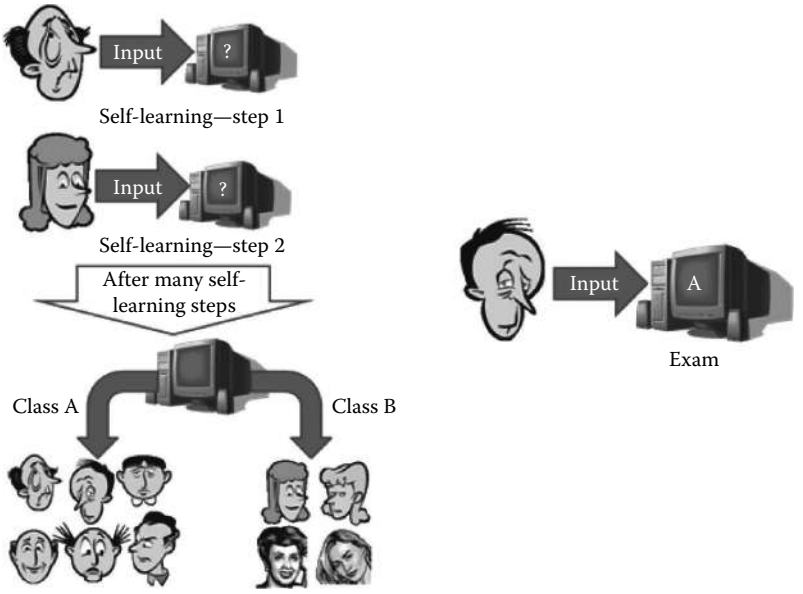

FIGURE 1.2 Classification problem with unsupervised learning used.

interesting approaches to solving clustering problems, and this problem can be thought of as the first step in building automatic systems capable of knowledge discovery, not only learning [CP07].

Let us discuss unsupervised learning scheme used for automatic solving of classification problems. During self-learning, the learned algorithm also receives information about features of the objects under consideration, but in this case, this input information is not enriched by accompanying information given by the teacher—because teacher is absent. Nevertheless, self-learning algorithm can perform classification of the objects using only similarity criteria and next can recognize new objects as belonging to particular self-defined classes.

1.6 Fuzzy Sets and Fuzzy Logic

One of the differences between the human mind and the computer relates to the nature of information/knowledge representation. Computers must have information in precise form, such as numbers, symbols, words, or even graphs; however, in each case, it must be an exact number, or a precisely selected symbol, or a properly expressed word or graph plotted in a precisely specified form, color, and dimension. Computers cannot accept a concept such as "integer number around 3," or "symbol that looks like a letter," etc. In contrast, human minds perform very effective thinking processes that take into account imprecise qualitative data (e.g., linguistic terms) but can come up with a good solution, which can be expressed sharply and precisely.

There are many examples showing the difference between mental categories (e.g., "young woman") and precisely computed values (e.g., age of particular people). Definitely, the relation between mathematical evaluation of age and "youngness" as a category cannot be expressed in a precise form. We cannot precisely answer the question, at which second of a girl's life she transforms to a woman, or at which exact hour her old age begins.

In every situation, when we need to implement in an intelligent system a part of human common sense, there is a contradiction between human fuzzy/soft thinking and the electronic system's sharp definition of data elements and use of precise algorithms. As is well known, the solution is to use fuzzy set and fuzzy logic methods [Z65]. Fuzzy set (e.g., the one we used above, "young woman") consists of the elements that, for sure (according to human experts), belongs to this set (e.g., 18-year-old graduate of

high school), and the elements that absolutely do not belong to this fuzzy set (e.g., 80-year-old grandma), but take into account the elements that belong to this set only partially. All elements that have degrees of membership different from zero belong to this particular fuzzy set. Some of them have membership function with values of 1—they belong to the set unconditionally. Elements with membership function have values of 0—they are outside of the set. For all other elements, the value of membership function is a real number between 0 and 1. The shape of membership function is defined by human experts (or sometimes from available data) but for practical computations, the preferred shapes are either triangular or trapezoidal.

Fuzzy logic formulas can be dually expressed by if … then … else … statements but they are expressed by means of fuzzy formulas. It is worth mentioning that fuzzy logic came into being as an extension of Lukasiewicz's multimodal logic [L20]. Details of this approach are described in other chapters.

It is worth mentioning here a gap between rather simple and easy-to-understand key ideas used in fuzzy data representation as well as simple fuzzy logic reasoning methods and rather complex practical problems solved in AI by means of fuzzy systems. It can be compared to walking in high mountains—first we go through a nice flowering meadow but after a while the walk transforms into extreme climbing.

Not all AI researchers like fuzzy methods. A well-known AI expert commented that this approach can be seen as "fuzzy theory about fuzzy sets." But in fact, the advantages of using fuzzy methods are evident. Not only the knowledge-based systems (i.e., expert systems) broadly use fuzzy logic and fuzzy representation of linguistic terms, but the fuzzy approach is very popular in economic data assessment, in medical diagnosis, and in automatic control systems. Moreover, their popularity increases because in many situations they are irreplaceable.

1.7 Genetic Algorithms and Evolutionary Computing

Figure 1.3 shows an example how the property of face image can be categorized. The face can be wide or narrow, can have large or small mouth, and eyes can be close or far. Once these categories are selected, each image of a face can be considered as a point in the three-dimensional space, as shown in Figure 1.4. Of course, often in the object we can distinguish more than just three properties and this would be a point

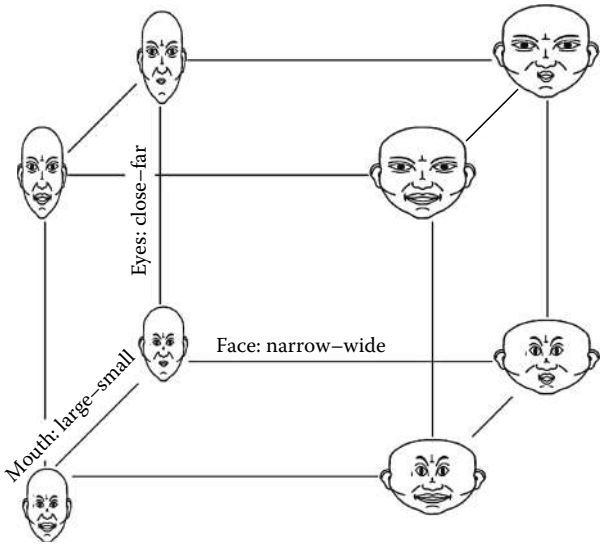

FIGURE 1.3 Example features that can be used for categorization and recognition of faces.

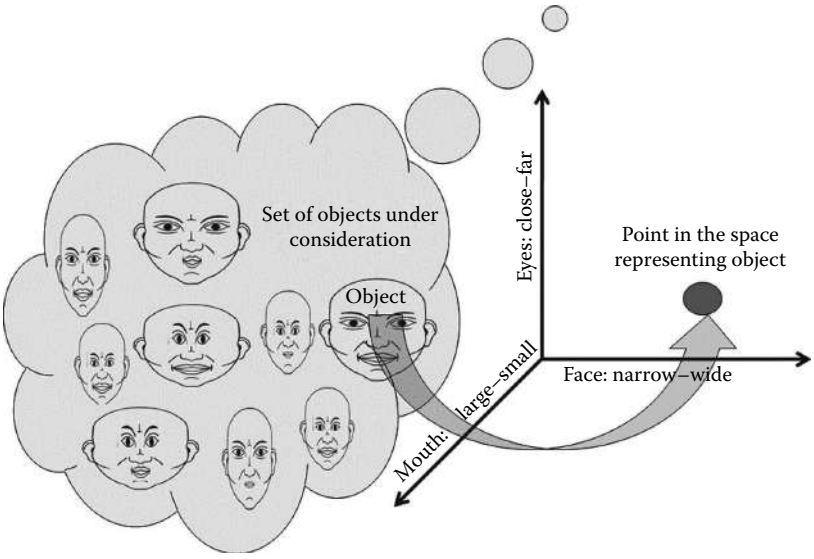

FIGURE 1.4 Relation between image of face and point in three-dimensional space.

in multidimensional space. Fuzzy systems may handle well the classifications when dimensionaliy they are limited to three. For problems with larger dimensions, neural networks have a significant advantage.

While describing neural networks, which are popular AI technology, we stressed their biological origin as a crude model of a part of a brain. Thanks to this fact, artificial neural networks exhibit brain-like behavior: they can learn and self-organize, generalize, and be used as predictors/classifiers, arrange information on the base of auto- and hetero-associative criteria, perform holistic and intuitive analysis of complex situations, are robust, etc. On the basis of the neural network example, we show the effectiveness of translating the biological knowledge into technological applications. Neural networks are obviously not a unique example of such biology-to-technology transmission of ideas. Another very well-known example is evolutionary computation [M96].

1.8 Evolutionary Computations and Other Biologically Inspired Methods for Problem Solving

The biological theory of evolution in many details (especially connected with the origin of humans) is still the area of hot discussions but no one questions the existence of evolution as a method of natural species optimization. In technology, we also seek for ever-better optimization methods. Existing optimization algorithms can be divided (freely speaking) into two subgroups. The first subgroup is formed by methods based on goal-oriented search (like fastest decrease/increase principle); an example is the gradient descent algorithm. The second group is based on random search methods; an example is the Monte Carlo method.

Both approaches to optimization suffer serious disadvantages. Methods based on goal-oriented search are fast and efficient in simple cases, but the solution may be wrong because of local minima (or maxima) of the criteria function. It is because the search process in all such methods is driven by local features of the criterion function, which is not optimal in the global sense. There is no method, which can be based on local properties of the optimization functionality and at the same time can effectively find the global optimum. On the other hand, the methods that use random searches can find proper solutions (optimal globally), but require long computational times. It is because the probability of a global optimum hit is very low and is increased only by means of performing a large number of attempts.

AI methods based on evolutionary computations combine random searches (because of using crossover and mutation) with goal-oriented searches (maximization of the fitness function, which is a functional to be optimized). Moreover, the search is performed simultaneously on many parallel paths because of several individuals (represented by chromosomes) belonging to every simulated population. The main idea of the evolutionary computing is based on defining all parameters and finding their optimal values. We generate (randomly) initial value for chromosomes (individuals belonging to the initial population) and then artificial evolution starts. Details of evolutionary computing are given in other chapters. It is worth to remember that evolutionary computing is a more general term than, e.g., genetic algorithms. Every user of genetic algorithms is doing evolutionary computing [K92].

In the title of this section, we mentioned that there exist other biologically inspired methods for problem solving. We note below just two that are very popular.

The first one is the ant colony optimization method that is used for solving many optimization problems, and is based on the ant's behavior. Like the neural network, it is a very simplified model of a part of the human brain, while genetic algorithms work on the basis of evolution, the ant's calculations use simplified model of the social dependences between ants in an ant colony. Every particular ant is a primitive organism and its behavior is also primitive and predictable. But the total ant population is able to perform very complicated tasks like the building of the complex three-dimensional structure of the anthill or finding the most efficient way for transportation of food from the source to the colony. The most efficient way can sometimes be equivalent to the shortest path; it takes into account the structure of the ground surface for minimizing the total effort necessary for food collection. Intelligence of the ant colony is its emerging feature. The source of very clever behavior observed sometimes for the whole ant population is located in rather simple rules controlling behavior of each particular ant and also in the simple rules governing relations and "communication" between ants. Both elements (e.g., mechanisms of single ant activity control as well as communication schemes functioning between ants) are easily modeled in the computer. Complex and purposeful behavior of the entire ant population can then be converted into an intelligent solution of a particular problem by the computer [CD91].

The second (too previously discussed) bio-inspired computational technique used in AI is an artificial immune systems methodology. The natural immune system is the strongest anti-intruder system that defends living organisms against bacteria, viruses, and other alien elements, which try to penetrate the organism. Natural immune systems can learn and must have memory, which is necessary for performing the above-mentioned activities. Artificial immune systems are models of this biological system that are able to perform similar activities on computer data, programs, and communication processes [CT02].

1.9 Intelligent Agents

Over many years of development of AI algorithms dedicated to solving particular problems, there was a big demand (in terms of computer calculation power and in memory). Therefore, programs with adjective "intelligent" were hosted on big computers and could not be moved from one computer to the other. An example is Deep Blue—a chess-playing computer developed by IBM—which, on May 11, 1997, won the chess world championship against Garry Kasparov.

In contemporary applications, AI, even the most successful, located in one particular place is not enough for practical problem solving. The future is distributed AI, ubiquitous intelligence, which can be realized by means of intelligent agents.

Agent technology is now very popular in many computer applications, because it is much easier to achieve good performance collaboratively, with limited costs by using many small but smart programs (agents) that perform some information gathering or processing task in a distributed computer environment working in the background. Typically, a particular agent is given a very small and well-defined task. Intelligent cooperation between agents can lead to high performance and high quality of the resulting services for the end users. The most important advantage of such an AI implementation is connected

with the fact that the intelligence is distributed across the whole system and is located in these places (e.g., Web sites or network nodes) when necessary [A02].

AI methods used on the base of agent technology are a bit similar to the ant colony methods described above. But an intelligent agent can be designed on the base of neural networks technology, can use elements taken from expert systems, can engage pattern recognition methods as well as clustering algorithms. Almost every earlier mentioned element of AI can be used in the intelligent agent technology as a realization framework.

The best-known applications of distributed AI implemented as a collection of cooperating but independent agents are in the area of knowledge gathering for Internet search machines. The second area of intelligent agent applications is related to spam detection and computer virus elimination tasks. Intelligent agent technology is on the rise and possibly will be the dominating form of AI in the future.

1.10 Other AI Systems of the Future: Hybrid Solutions

In the previous sections, we tried to describe some "islands" from the "AI archipelago." Such islands, like neural networks, fuzzy sets, or genetic algorithms are different in many aspects: their theoretical background, technology used, data representation, methods of problem solving, and so on. However, many AI methods are complementary, not competitive. Therefore many modern solutions are based on the combination of these approaches and use hybrid structures, combining the best elements taken from more than one group of methods for establishing the best solution. In fact, AI elements can be combined in any arrangement because they are flexible. The very popular hybrid combinations are listed below:

- Neuro-fuzzy systems, which are based on fuzzy systems intuitive methodology combined with neural networks power of learning
- Expert systems powered by fuzzy logic methods for conclusion derivations
- Genetic algorithms used for the selection of the best neural network structure

Hybridization can be extended to other combinations of AI elements that when put together work more effectively than when used separately. Known are hybrid constructions combining neural networks with other methods used for data classification and pattern recognition. Sometimes, expert systems are combined not only with fuzzy logic but also with neural networks, which can collect knowledge during its learning process and then put it (after proper transformation) as an additional element in the knowledge base–powered expert system. Artificial immune systems can cooperate with cluster analysis methods for proper classification of complex data [CA08].

Nobody can foretell how AI will develop in the future. Perhaps AI and computational intelligence will go toward automatic understanding technologies, developed by the author and described in [TO08]? This chapter was meant to provide a general overview of AI and electronic engineering, and enriched with this information the reader can hopefully be better suited to find proper tools for specific applications.

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