Neural Networks and Micromechanics

Ernst Kussul • Tatiana Baidyk •
Donald C. Wunsch

Neural Networks and Micromechanics

Springer

Prof. Ernst Kussul
Center of Applied Research and
Technological Development
Autonomous National University of
Mexico (UNAM)
Mexico
ekussul@servidor.unam.mx

Prof. Tatiana Baidyk
Center of Applied Research and
Technological Development
Autonomous National University of
Mexico (UNAM)
Mexico
t.baydyk@ccadet.unam.mx

Prof. Donald C. Wunsch II
Dept. of Electrical and Computer
Engineering
Missouri University of Science
and Technology
Rolla, USA
dwunsch@mst.edu

ACM Computing Classification (1998): I.2, I.4, I.5, C.3

ISBN: 978-3-642-02534-1   e-ISBN: 978-3-642-02535-8
DOI 10.1007/978-3-642-02535-8
Springer Heidelberg Dordrecht London New York

Library of Congress Control Number: 2009938014

Cover design: KuenkelLopka, Heidelberg, Germany

Printed on acid-free paper

Springer is part of Springer Science+Business Media (www.springer.com)

Preface

Micromechanical manufacturing based on microequipment creates new possibilities in goods production. If microequipment sizes are comparable to the sizes of the microdevices to be produced, it is possible to decrease the cost of production drastically. The main components of the production cost - material, energy, space consumption, equipment, and maintenance - decrease with the scaling down of equipment sizes. To obtain really inexpensive production, labor costs must be reduced to almost zero. For this purpose, fully automated microfactories will be developed.

To create fully automated microfactories, we propose using artificial neural networks having different structures. The simplest perceptron-like neural network can be used at the lowest levels of microfactory control systems. Adaptive Critic Design, based on neural network models of the microfactory objects, can be used for manufacturing process optimization, while associative-projective neural networks and networks like ART could be used for the highest levels of control systems.

We have examined the performance of different neural networks in traditional image recognition tasks and in problems that appear in micromechanical manufacturing. We and our colleagues also have developed an approach to microequipment creation in the form of sequential generations. Each subsequent generation must be of a smaller size than the previous ones and must be made by previous generations. Prototypes of first-generation microequipment have been developed and assessed.

Interaction between neural networks and micromechanics does not have only one direction – while neural networks are helpful in micromechanics, micromechanics also can help to find new applications for neural networks. Currently, it is difficult to examine the effectiveness of neural networks in mechanical industry automation because each experiment in a mechanical factory is very expensive. Micromechanical factories will help us to examine different neural networks, compare them in mechanical production tasks, and recommend their use in conventional mechanics.

The results given in this book permit us to estimate optimistically the perspectives of neural network applications in micromechanics.

We have been working on neural networks, image recognition, and micromechanics for many years. Support from the National Academy of Sciences of the Ukraine, from the European Union (projects INTAS), from CONACYT and DGAPA (UNAM) in Mexico, from the US National Science Foundation the Mary K. Finley Endowment, the Missouri S&T Intelligent Systems Center, and from the company WACOM in Japan is gratefully acknowledged.

We want to thank our collaborators from the Ukraine and from Mexico for helping us bring this interesting project to fruition.

Finally, Ernst Kussul would like to thank his family; Tatiana Baidyk would like to thank her son Oleksandr Makeyev, her mother Mariya Baidyk and her sister Olga Malinina; and Don Wunsch would like to thank Hong and Donnie. Without their encouragement, understanding, and patience, this book would not exist.

E. Kussul, T. Baidyk, D. C. Wunsch

Contents

Chapter 1
Introduction

The title of the book, "Neural Networks and Micromechanics," seems artificial. However, the scientific and technological developments in recent decades demonstrate a very close connection between the two different areas of neural networks and micromechanics. The purpose of this book is to demonstrate this connection.

Some artificial intelligence (AI) methods, including neural networks, could be used to improve automation system performance in manufacturing processes. However, the implementation of these AI methods within industry is rather slow because of the high cost of conducting experiments using conventional manufacturing and AI systems. To lower the cost, we have developed special micromechanical equipment that is similar to conventional mechanical equipment but of much smaller size and therefore of lower cost. This equipment could be used to evaluate different AI methods in an easy and inexpensive way. The proved methods could be transferred to industry through appropriate scaling. In this book, we describe the prototypes of low cost microequipment for manufacturing processes and the implementation of some AI methods to increase precision, such as computer vision systems based on neural networks for microdevice assembly and genetic algorithms for microequipment characterization and the increase of microequipment precision.

The development of AI technologies opens an opportunity to use them not only for conventional applications (expert systems, intelligent data bases [1], technical diagnostics [2, 3] etc.), but also for total automation of mechanical manufacturing. Such AI methods as adaptive critic design [4, 5], neural network-based computer vision systems [6–10], etc. could be used to solve automation problems. To examine this opportunity, it is necessary to create an experimental factory with fully-automated manufacturing processes. This is a very difficult and expensive task.

To make very small mechanical microequipment, a new technology was proposed [11–14]. This technology is based on micromachine tools and microassembly devices, which can be produced as sequential generations of microequipment. Each generation should include equipment (machine tools, manipulators, assembly devices, measuring instruments, etc.) sufficient for manufacturing identical but smaller equipment. Each subsequent equipment generation could be produced by

E. Kussul et al. *Neural Networks and Micromechanics*,
DOI 10.1007/978-3-642-02535-8_1,

the preceding one. The size of each subsequent generation's equipment is smaller than the overall size of the preceding generation.

The first-generation microequipment can be produced by conventional large-scale equipment. Using microequipment of this first generation, a second micro-equipment generation having smaller overall sizes can be produced.

We call this approach to mechanical microdevice manufacturing Microequipment Technology (MET) [15].

The proposed MET technology has many advantages:

(1) The equipment miniaturization leads to decreasing the occupied space as well as energy consumption, and, therefore, the cost of the products.
(2) The labor costs are bound to decrease due to the reduction of maintenance costs and a higher level of automation expected in MET.
(3) Miniaturization of equipment by MET results in a decrease of its cost. This is a consequence of the fact that microequipment itself becomes the object of MET. The realization of universal microequipment that is capable of extended reproduction of itself will allow the manufacture of low-cost microequipment in a few reproductive acts because of the lower consumption of' materials, energy, labor, and space in MET. Thus, the miniaturization of equipment opens the way to a drastic decrease in the unit cost of individual processing.

At a lower unit cost of individual micromachining, the most natural way to achieve high throughput is to parallelize the processes of individual machining by concurrent use of a great quantity of the same kind of microequipment. Exploitation of that great number of microsized machine tools is only feasible with their automatic operation and a highly automated control of the microfactory as a whole. We expect that many useful and proved concepts, ideas, and techniques of automation can be borrowed from mechanical engineering. They vary from the principles of factory automation (FMS and CAM) to the ideas of unified containers, clamping devices, and techniques of numerical control. However, the automation of micromanufacturing has peculiarities that will require the special methods of artificial intelligence.

Let us consider a general hierarchical structure of the automatic control system for a micromechanical factory. The lowest (first) level of the system controls the micromechanical equipment (the micromachine tools and assembly manipulators) and provides the simplest microequipment diagnostics and the final measurement and testing of production. The second level of the control system controls the devices that transport workpieces, tools, parts, and all equipment items; coordinates the operation of the lowest level devices; and provides the intermediate quality inspection of production and the more advanced diagnostics of equipment condition. The third control level contains the system for the automatic choice of process modes and routes for machining parts. The top (fourth) level of the control system detects non-standard and alarm situations and makes decisions regarding these situations, including communication with the operator.

We proceed from the assumption that no more than one operator will manage the microfactory. This means that almost all the problems arising at any control level during the production process should be solved automatically and that the operator must solve only a few problems, those that are too complex or unusual to be solved automatically. Since any production process is affected by various disturbances, the control system should be an adaptive one. Moreover, it should be self-learning because it is impossible to foresee all kinds of disturbances in advance. AI that is able to construct the self-learning algorithms and to minimize the participation of the operator appears especially useful for this task. AI includes different methods for creating autonomous control systems. The neural classifiers will be particularly useful at the lowest level of the control system. They could be used to select treatment modes, check cutting tool conditions, control assembly processes, etc. They allow for more flexibility in the control system. The system will automatically compensate for small deviations of production conditions, such as a change in the cutting tool's shape or external environment parameters, variations in the structure of workpiece materials, etc. AI will permit the design of self-learning classifiers and should provide the opportunity to exclude the participation of a human operator at this level of control.

At the second control level, the AI system should detect all deviations from the normal production process and make decisions about how to modify the process to compensate for the deviation. The compensation should be made by tuning the parameters of the lower-level control systems. Examples of such deviations are deviations from the production schedule, failures in some devices, and off-standard production. At this level, the AI system should contain the structures in which the interrelations of production process constituents are represented. As in the previous case, it is desirable to have the algorithms working without the supervisor.

The third control level is connected basically with the change of nomenclature or volume of the production manufactured by the factory. It is convenient to develop such a system so that the set-up costs for a new production or the costs to change the production volume are minimal. The self-learning AI structures formed at the lowest level could provide the basis for such changes of set-up by selection of the process parameters, the choice of equipment configuration for machining and assembly, etc. At the third control level, the AI structures should detect the similarity of new products with the products that were manufactured in the past. On the basis of this similarity, the proposals about the manufacturing schedule, process modes, routing, etc. will be automatically formed and then checked by the usual computational methods of computer aided manufacturing (CAM). The results of the check, as well as the subsequent information about the efficiency of decisions made at this level, may be used for improving the AI system.

The most complicated AI structures should be applied at the top control level. This AI system level must have the ability to reveal the recent unusual features in the production process, to evaluate the possible influence of these new features on the production process, and to make decisions about changing the control system parameters at the various hierarchical levels or for calling for the operator's help. At this level, the control system should contain the intelligence knowledge base, which can be created using the results of the operation of the lower-level control systems and knowledge from experts. At the beginning, expert knowledge of macromechanics may be used.

At present, many methods of AI are successfully used in industry [16, 17], Some of these also could be used for micromechanics. Though the problems of fully-automated factory creation cannot be investigated experimentally in conventional industry because of the high cost of the experiments, here we propose to develop a low-cost micromechanical test bed to solve these problems.

The first prototype of the first generation was designed and manufactured at the International Research and Training Centre of Information Technologies, which is a part of V. M. Glushkov Cybernetics Center, Ukraine.

The second prototype of the first generation microequipment was designed and examined in CCADET, UNAM. The prototypes use adaptive algorithms of the lowest level.

At present, more sophisticated algorithms based on neural networks and genetic algorithms are being developed. Below, we describe our experiments in the area of the development and applications of such algorithms.

This book is intended as a professional reference and also as a textbook for graduate students in science, engineering, and micromechanics. We expect it to be particularly interesting to computer scientists and applied mathematicians applying it to neural networks, artificial intelligence, image recognition, and adaptive control, among many other fields.

References

1. Eberhart R., Overview of Computational Intelligence and Biomedical Engineering Applications, Proceedings of the 20th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 3, 1998, pp. 1125–1129.
2. Hui T., Brown D., Haynes B., Xinxian Wang, Embedded E-diagnostic for Distributed Industrial Machinery, IEEE International Symposium on Computational Intelligence for Measurement Systems and Applications, 2003, pp. 156–161.
3. Awadallah M., Morcos M., Application of AI Tools in Fault Diagnosis of Electrical Machines and Drives. An Overview, *IEEE Transactions on Energy Conversio*n, 18, Issue 2, 2003, pp. 245–251.
4. Werbos P., Advanced Forecasting Methods for Global Crisis Warning and Models of Intelligence. In: General Systems Yearbook, 22, 1977, pp. 25–38.
5. Prokhorov D., Wunsch D., Adaptive Critic Designs, *IEEE Transactions on Neural Networks*, 8, No. 5, 1997, pp. 997–1007.
6. Bottou L., Cortes C., Denker J., Drucker H., Guyon L., Jackel L., LeCun J., Muller U., Sackinger E., Simard P., Vapnik V., Comparison of Classifier Methods: A Case Study in Handwritten Digit Recognition. In: Proceedings of 12th IAPR International Conference on Pattern Recognition, 2, 1994, pp. 77–82.
7. Fukushima, K., Neocognitron: A Hierarchical Neural Network Capable of Visual Pattern Recognition, *Neural Networks*, 1, 1988, pp. 119–130.
8. Roska T., Rodriguez-Vazquez A., Toward Visual Microprocessors, Proceedings of the IEEE 90, Issue 7, July 2002, pp. 1244–1257.

9. Baidyk T., Application of Flat Image Recognition Technique for Automation of Micro Device Production, Proceedings of the International Conference on Advanced Intelligent Mechatronics AIM 2001, Italy, 2001, pp. 488–494.
10. Baidyk T., Kussul E., Makeyev O., Caballero A., Ruiz L., Carrera G., Velasco G., Flat Image Recognition in the Process of Microdevice Assembly, *Pattern Recognition Letters*, 25/1, 2004, pp. 107–118.
11. Kussul E., Micromechanics and the Perspectives of Neurocomputing. In: Neuron-like Networks and Neurocomputers, Kiev, Ukraine, 1993, pp. 66–75 (in Russian).
12. Kussul E., Rachkovskij D., Baidyk T., Talayev S., Micromechanical Engineering: A Basis for the Low-cost Manufacturing of Mechanical Microdevices Using Microequipment, *Journal of Micromechanics and Microengineering*, 6, 1996, pp. 410–425.
13. Kussul E.M., Rachkovskij D.A., Kasatkin A.M., Kasatkina L.M., Baidyk T.N., Lukovich V.V., Olshanikov V.S., Talayev S.A., Neural Network Applications in Micro Mechanics, Neural Systems of Information Processing, Kiev, 1996, Vol. 1, pp. 80–88 (in Russian).
14. Kussul E.M., Micromechanics as a New Area of Neural Network Applications. Proceedings of the 5th European Congress on Intelligent Techniques and Soft Computing. Aachen, Germany, 1997, Vol.1 pp. 521–523.
15. Kussul, E., Baidyk, T., Ruiz-Huerta, L., Caballero, A., Velasco, G., Kasatkina, L.: Development of Micromachine Tool Prototypes for Microfactories. *Journal of Micromechanics and Microengineering*, 12, 2002, pp. 795–812.
16. Wenxin Liu., Venayagamoorthy G., Wunsch D., A Heuristic Dynamic Programming Based Power System Stabilizer for a Turbogenerator in a Single Machine Power System. 39th IAS Annual Meeting on Industry Applications, 1, 2003, pp. 270–276.
17. Croce, F., Delfino, B., et al.: Operations and Management of the Electric System for Industrial Plants: An Expert System Prototype for Load-Shedding Operator Assistance. *IEEE Transactions on Industry Applications* 37, Issue 3, 2001, pp. 701–708.

Chapter 2
Classical Neural Networks

During the last few decades, neural networks have moved from theory to offering solutions for industrial and commercial problems. Many people are interested in neural networks from many different perspectives. Engineers use them to build practical systems to solve industrial problems. For example, neural networks can be used for the control of industrial processes.

There are many publications that relate to the neural network theme. Every year, tens or even hundreds of international conferences, symposiums, congresses, and seminars take place in the world. As an introduction to this theme we can recommend the books of Robert Hecht-Nielsen [1], Teuvo Kohonen [2], and Philip Wasserman [3], and a more advanced book that is oriented on the applications of neural networks and is edited by A. Browne [4]. In this book it is assumed that the reader has some previous knowledge of neural networks and an understanding of their basic mechanisms. In this section we want to present a very short introduction to neural networks and to highlight the most important moments in neural network development.

2.1 Neural Network History

Attempts to model the human brain appeared with the creation of the first computer. Neural network paradigms were used for sensor processing, pattern recognition, data analysis, control, etc. We analyze, in short, different approaches for neural network development.

2.2 McCulloch and Pitts Neural Networks

The paper of McCulloch and Pitts [5] was the first attempt to understand the functions of the nervous system. For explanation, they used very simple types of neural networks, and they formulated the following five assumptions according to the neuron operation:

E. Kussul et al., *Neural Networks and Micromechanics*,
DOI 10.1007/978-3-642-02535-8_2, © Springer-Verlag Berlin Heidelberg 2010