

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

© Springer-Verlag Berlin Heidelberg 2010

This work is subject to copyright. All rights are reserved, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilm or in any other way, and storage in data banks. Duplication of this publication or parts thereof is permitted only under the provisions of the German Copyright Law of September 9, 1965, in its current version, and permission for use must always be obtained from Springer. Violations are liable to prosecution under the German Copyright Law.

The use of general descriptive names, registered names, trademarks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.

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

1	Introduction	1
	References	4
2	Classical Neural Networks	7
2.1	Neural Network History	7
2.2	McCulloch and Pitts Neural Networks	7
2.3	Hebb Theory	8
2.4	Perceptrons	10
2.5	Neural Networks of the 1980s	12
2.6	Modern Applications of Neural Network Paradigms	15
2.6.1	Hopfield Neural Networks	15
2.6.2	Adaptive Resonance Theory (ART)	16
2.6.3	Self-Organizing Feature Map (SOFM) Neural Networks	17
2.6.4	Cognitron and Neocognitron	18
2.6.5	Backpropagation	19
2.6.6	Adaptive Critic Design	20
2.7	RTC, RSC, LIRA and PCNC Neural Classifiers	21
	References	21
3	Neural Classifiers	27
3.1	RTC and RSC Neural Classifiers for Texture Recognition	27
3.1.1	Random Threshold Neural Classifier	29
3.1.2	Random Subspace Classifier	31
3.1.3	Encoder of Features	32
3.2	LIRA Neural Classifier for Handwritten Digit Recognition	33
3.2.1	Rosenblatt Perceptrons	34
3.2.2	Description of the Rosenblatt Perceptron Modifications	35
3.3	LIRA-Grayscale Neural Classifier	41
3.4	Handwritten Digit Recognition Results for LIRA-Binary	42
3.5	Handwritten Digit Recognition Results for the LIRA-Grayscale	43

3.6 Discussion 44

References 45

4 Permutation Coding Technique for Image Recognition System 47

4.1 Special- and General-Purpose Image Recognition Systems. 47

4.2 Random Local Descriptors. 49

4.3 General-Purpose Image Recognition System Description 50

4.4 Computer Simulation 54

4.5 Permutation Coding Neural Classifier (PCNC). 54

 4.5.1 PCNC structure. 54

 4.5.2 Feature extractor 55

 4.5.3 Encoder 56

4.6 PCNC Neural Classifier Training 64

4.7 Results Obtained on the MNIST Database 66

4.8 Results Obtained on the ORL Database 69

References 71

5 Associative-Projective Neural Networks (APNNs) 75

5.1 General Description of the Architecture 75

 5.1.1 Neuron, the Training Algorithms. 75

 5.1.2 Neural Fields 78

5.2 Input Coding and the Formation of the Input Ensembles 83

 5.2.1 Local Connected Coding 83

 5.2.2 Shift Coding 88

 5.2.3 Functions of Neural Ensembles 96

 5.2.4 Methods of Economical Presentation of the
 Matrix of Synaptic Weights (Modular Structure) 98

5.3 Conclusion. 102

References 103

**6 Recognition of Textures, Object Shapes, and
Handwritten Words 105**

6.1 Recognition of Textures. 105

 6.1.1 Extraction of Texture Features 105

 6.1.2 The Coding of Texture Features 106

 6.1.3 Texture Recognition 107

 6.1.4 The Experimental Investigation of the Texture
 Recognition System 109

 6.1.5 Texture Recognition with the Method of Potential
 Functions 111

6.2 Recognition of Object Shapes 113

 6.2.1 Features for Complex Shape Recognition 114

 6.2.2 Experiments with Algorithms of Complex
 Shape Recognition 116

- 6.3 Recognition of Handwritten Symbols and Words 117
 - 6.3.1 Features Utilized for the Recognition of Handwritten Words. 117
- 6.4 Conclusion. 127
- References 128

- 7 Hardware for Neural Networks 131**
 - 7.1 NIC Neurocomputer NIC 131
 - 7.1.1 Description of the Block Diagram of the Neurocomputer 131
 - 7.1.2 The Realization of the Algorithm of the Neural Network on the Neurocomputer 133
 - 7.2 Neurocomputer B-512 134
 - 7.2.1 The Designation of the Neurocomputer Emulator 135
 - 7.2.2 The Structure of the Emulator 135
 - 7.2.3 The Block Diagram of B-512 138
 - 7.3 Conclusion. 140
 - References 140

- 8 Micromechanics 141**
 - 8.1 The Main Problems in Microfactory Creation 141
 - 8.2 General Rules for Scaling Down Micromechanical Device Parameters 145
 - 8.3 Analysis of Micromachine Tool Errors. 148
 - 8.3.1 Thermal Expansion. 148
 - 8.3.2 Rigidity. 150
 - 8.3.3 Forces of Inertia 153
 - 8.3.4 Magnetic Forces 155
 - 8.3.5 Electrostatic Forces. 155
 - 8.3.6 Viscosity and Velocity of Flow 156
 - 8.3.7 Mass Forces 159
 - 8.3.8 Forces of Cutting 159
 - 8.3.9 Elastic Deformations. 161
 - 8.3.10 Vibrations 162
 - 8.4 The First Prototype of the Micromachine Tool. 164
 - 8.5 The Second Prototype 167
 - 8.6 The Second Micromachine Tool Prototype Characterization 169
 - 8.6.1 Positional Characteristics 170
 - 8.6.2 Geometric Inspection 177
 - 8.7 Errors That Do Not Decrease Automatically 178
 - 8.7.1 Methods of Error Correction 178
 - 8.8 Adaptive Algorithms 181
 - 8.8.1 Adaptive Algorithms Based on a Contact Sensor. 181
 - 8.9 Possible Applications of Micromachine Tools 185
 - 8.9.1 The Problem of Liquid and Gas Fine Filtration 185

8.9.2 Design of Filters with a High Relation of Throughput to Pressure Drop	186
8.9.3 An Example of Filter Design.	188
8.9.4 The Problems of Fine Filter Manufacturing.	188
8.9.5 The Filter Prototype Manufactured by the Second Micromachine Tool Prototype.	189
8.9.6 Case Study	189
8.10 Conclusion.	191
References	192
9 Applications of Neural Networks in Micromechanics	195
9.1 Neural-Network-Based Vision System for Microworkpiece Manufacturing	195
9.2 The Problems in Adaptive Cutting Processes	196
9.3 Permutation Coding Neural Classifier	197
9.3.1 Feature Extractor.	197
9.3.2 Encoder	199
9.3.3 Neural Classifier	201
9.4 Results.	202
References	203
10 Texture Recognition in Micromechanics	205
10.1 Metal Surface Texture Recognition	205
10.2 Feature Extraction	207
10.3 Encoder of Features	207
10.4 Results of Texture Recognition	208
References	209
11 Adaptive Algorithms Based on Technical Vision	211
11.1 Microassembly Task	211
11.2 LIRA Neural Classifier for Pin-Hole Position Detection.	216
11.3 Neural Interpolator for Pin-Hole Position Detection	217
11.4 Discussion	220
References	221

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

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 microequipment 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 Conversion*, 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., Olshaniikov 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: