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10 - 13 September 2007

## FACULTY OF
## COMPUTER SCIENCE AND AUTOMATION

# COMPUTER SCIENCE MEETS AUTOMATION

## VOLUME I

**Session 1 - Systems Engineering and Intelligent Systems**

**Session 2 - Advances in Control Theory and Control Engineering**

**Session 3 - Optimisation and Management of Complex Systems and Networked Systems**

**Session 4 - Intelligent Vehicles and Mobile Systems**

**Session 5 - Robotics and Motion Systems**

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# Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

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## 2 Advances in Control Theory and Control Engineering

$52^{\text{nd}}$ Internationales Wissenschaftliches Kolloquium
Technische Universität Ilmenau
10 – 13 September 2007

O. G. Rudenko / A. A. Bessonov / P. Otto

# A Method for Information Coding in CMAC Networks

## 1. Introduction

An artificial neural network in form of a **CMAC** net (**C**erebellar **M**odel **A**rticulation **C**ontroller), which was developed firstly for the regulation of robot manipulators [ 1,2 ], is characterized by large learning speed, simple realization and the possibility of influencing the necessary memory capacity purposefully [ 3-6 ]. The main difference between CMAC nets and the majority of other network types lies in the possibility of selection of a relatively large number of free parameters of the net (methods of the information coding, number of the quantization stages and level of quantization, kind of the activation functions of the neurons). While the problem of the effective choice of the basic functions of the neurons has been given large attention [ 7-9 ], the problem of the optimal selection of the other parameters of the net has so far hardly been attended. This work is therefore dedicated to the investigation of methods for selection of patterns to information coding in a CMAC net.

## 2. Structure of a CMAC Network

The net consists of the input -, a hidden and an output layer, denoted by $\mathrm{L1}$, $\mathrm{L2}$ and $\mathrm{L3}$ respectively (fig. 1). The layer $\mathrm{L1}$ has $R_i$ quantization level with a quantization step $r_i$ for each input $i$. In addition all quantization levels of the $i^{\text{th}}$ inputs have the same number of $\rho$ quantization stages $(C_1^i, C_2^i, \dots, C_\rho^i)$, from which each includes $\rho^* \leq \rho$ quantization ranges $\mathrm{A}, \mathrm{B}, \dots, \mathrm{a}, \mathrm{b}, \dots$ to which a priori selected basic functions are assigned. Therefore the quantization ranges can be taken as neurons of the input layer and the basic functions can be regarded as their activation functions. A n-dimensional input vector $\boldsymbol{x}$ activates $N\rho$ neurons of $\mathrm{L1}$.

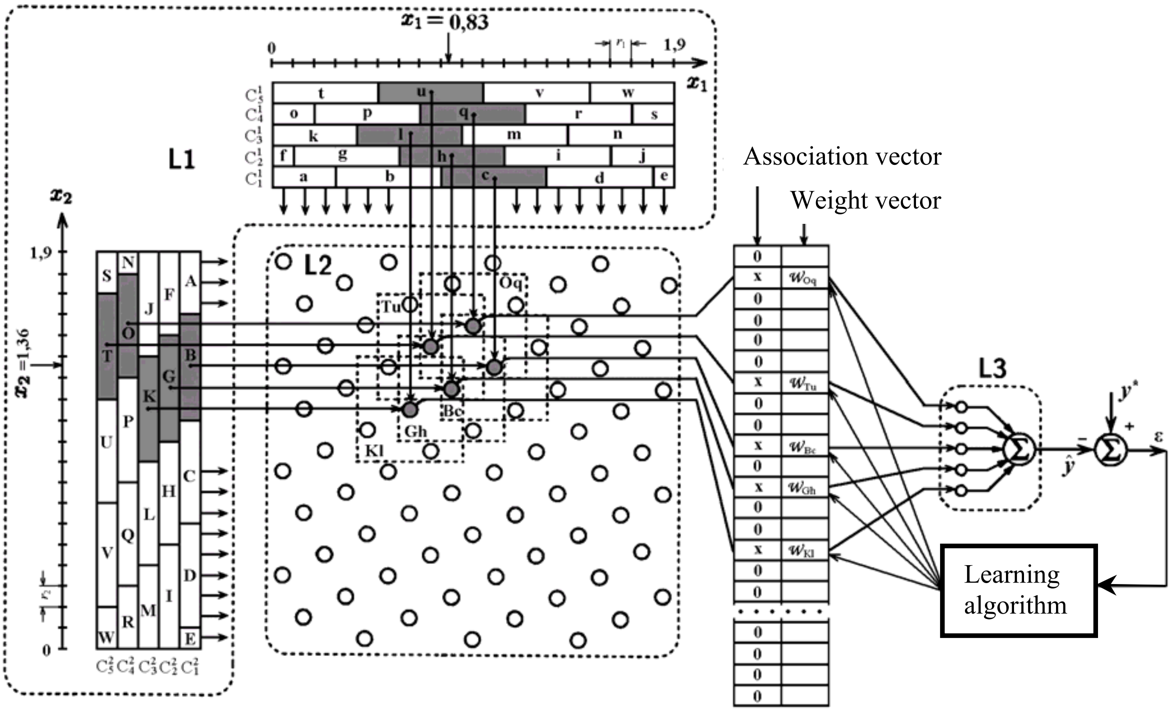


Fig 1: Structure of a CMAC Network

The layer L2 consists of associative neurons, which are connected with certain neurons of the layer L1 and whose working ranges combine. The maximum number of associative neurons is given by the equation

$$n_{\max} = \left]\rho\left(\frac{R-1}{\rho}+1\right)^{N}\right[ \quad , \tag{1}$$

where $R$ – is the Number of quantization levels of the input signals,

$N$ – is the dimension of the input vector,

$]\bullet[$ - designates the round to the next larger whole number.

Each neuron in L2 has its own receptor field, which includes further ($\rho - 1$) associative neurons. A signal deviating from zero leads to the excitation of $\rho$ associative neurons, which supply output signals, which correspond to the product of the signals arriving from the neurons of the layer L1. All neurons of the output layer L3 are connected with the associative neurons of the second layer. Each connection has its own adaptive weight $w_i \; (i = \overline{1,n})$. The output signal of the third layer arises therefore as weighted sum of the output signals of the second layer. The transformation $\mathbf{a} = S(\mathbf{x})$ codes the information (layer L1 and L2) and the transformation $\hat{\mathbf{y}} = P(\mathbf{a}) = \mathbf{a}^{\mathrm{T}}\mathbf{w}$ computes the output signal (layer L3).

## 3. Choice of Activation function

By a non- rectangular activation functions, the output signal is computed using

$$\hat{y} = H(\boldsymbol{a}^T\boldsymbol{\Phi}(\boldsymbol{x}))\boldsymbol{w}, \qquad \text{with} \quad \boldsymbol{\Phi}(\boldsymbol{x})=diag(\boldsymbol{\Phi}_1(\boldsymbol{x}), \boldsymbol{\Phi}_2(\boldsymbol{x}), \ldots \boldsymbol{\Phi}_n(\boldsymbol{x})), \tag{2}$$

and $\Phi_i(x) = \prod_{j=1}^{N} \phi_{ij}(x_j)$; $\phi_{ij}(x_j)$ - is the value of the activation function in $x_j$.

In CMAC nets with rectangular basic functions is $\boldsymbol{\Phi}(\boldsymbol{x})=\boldsymbol{I}$. The elements of the association vector have only the values 0 or 1. However, for high requirements of the precision of the models they are not suitable. Learning occurs in CMAC nets in the change of the weight vector $\boldsymbol{w}$ by comparison of the reaction of the net $\hat{y}(k)$ with for a learning example $\{\boldsymbol{x}(k), \boldsymbol{y}^*(k)\}$ given output value $\boldsymbol{y}^*(k)$. The learning algorithm reads:

$$w(k+1) = w(k) + \frac{y^*(k) - \hat{y}(k)}{\left\|\Phi(x(k))a(k)\right\|^2}\Phi(x(k))a(k). \tag{3}$$

Frequently Gauss' curves are used as activation functions. It is however difficult to specify the excitation borders exactly what is important for coding the information. The cosine function avoids this disadvantage

$$\Phi_i(x_j) = \begin{cases} \cos\left(\frac{\pi}{\rho \mathrm{r_j}}\left(x_j - \lambda_i\right)\right); & x_j \in (\lambda_i - \frac{\rho \mathrm{r_j}}{2}, \lambda_i + \frac{\rho \mathrm{r_j}}{2}]. \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

## 4. Information coding

A special coding makes a substantial decrease in memory requirement for CMAC nets possible. In the layers L1 and L2 a coding is done, with which for each *N*- dimensional input vector $\boldsymbol{x}(i)$ using the association layer a *n*- dimensional association vector $\boldsymbol{a}(i)$ is formed. Its elements are assumed to be from the interval [0, 1]. Only $\rho << n$ elements of this vector have values not equal zero, i.e. only $\rho$ memory elements are active. Coding takes place in two steps: First in the layer L1 a discretization is made via quantization of the input signals and secondly the code is computed in the layer L2. Thereby the mutual arrangement of the neurons of the input layer is important, which belong to different quantization stages, because herewith the coding pattern is clearly determined.

With non rectangular basic functions a problem develops with the selection of the coding pattern. The simplest coding method is the use of a table, in which $\rho$=1 is selected. A maximum memory volume of $R^N$ memory locations is required. This coding pattern is suitable only for rectangular affiliation functions, because for all other types the receptive fields of the associative neurons do not overlap. Learning is unnecessary thereby because simply the value of the function can be registered in the appropriate place of the association vector. If the quantization patterns are alike concerning all components of the vector of the output signals, the associative neurons will be arranged diagonally. Here the maxima are likewise for non-rectangular basic functions on the diagonals, which makes learning in points between the diagonals more difficult and substantially worsens the filter characteristics of the net.
Exchanging some neuron layers in the quantization matrices (fig. 1), permits a change of the coding pattern. With the same signal the same neurons will be excited, while the receptive fields of the associative neurons are completely differently arranged. Since no pronounced diagonal arrangement of the associative neurons is to be registered here, the approximation accuracy becomes substantially larger. At present there are still no recommendations regarding the optimal choice of the coding pattern. It is experimentally determined. It must be paid attention nevertheless to the fact that any neuron of a certain stage $C_k^i$ of the input layer should not be connected to more than ( $\rho - 1$ )neurons of the neighbour layers $C_{k-1}^i$ and $C_{k+1}^i$. This corresponds to a delimitation of the association vector on maximally ($\rho$-1) components for coding of two different vectors of the input signals, for which a recognition is still possible.

## 5. Simulative Experiments

A goal is the investigation of the influence of the coding pattern on the identification and the control of the nonlinear system expressed by equation (5) when disturbed by white noise in the interval [-0,3 0,3].

$$y(k+1) = 0.725\beta \sin\left( \frac{16u(k) + 8y(k)}{\beta\left(3 + 4u^2(k) + 4y^2(k)\right)} \right) + 0.2u(k) + 0.2y(k), \tag{5}$$

After the identification with 30000 examples with $\beta = 0{,}8$, basic functions according to equation (4) and the desired controlled variable

$$y^*(k) = 0.48 + 0.07\sin(\pi k/200) - 0.05\cos(\pi k/100)\,,$$

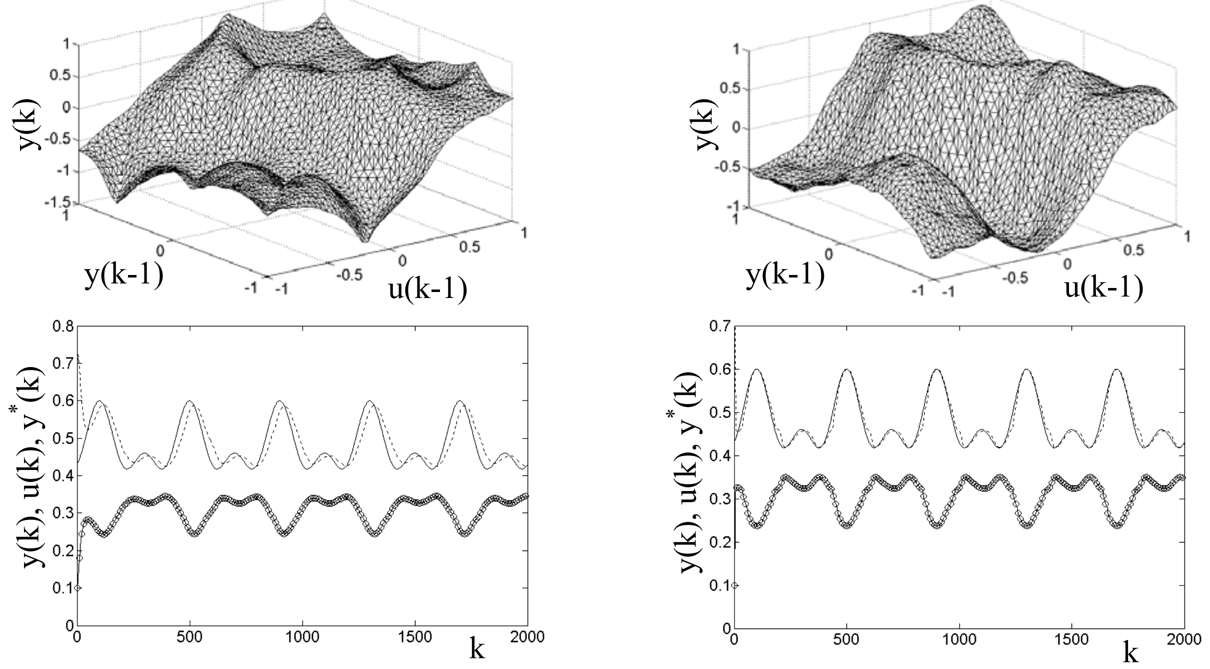
stationary, evenly distributed random signal *u*(*k*) from the interval [ - 1, 1 ] and the parameters of the net *R=50*, *ρ = 20,* which requires 238 memory locations, the control was performed using the following algorithm:

$$u(k+1) = u(k) + \gamma\nabla_u \hat{y}(k) e_y(k)\,, \qquad (6)$$

with γ – the incrementation (affects the convergence speed);

$$\nabla_u \hat{y}(k) = \frac{\partial \hat{y}}{\partial u(k)} = \sum_{i=1}^{n}\left[ a_i w_i \left( \prod_{\substack{j=1 \\ j\neq k}}^{N} \phi_{ij}(\hat{y}(k-1)) \right) \frac{\partial \phi_{ik}}{\partial u(k)} \right]; \qquad e_y(k) = y^*(k) - \hat{y}(k)\,.$$

Fig. 5a shows the results of the identification (upper diagram) and the control (lower diagram) by using the "diagonal" and fig. 5b by using the random coding pattern accordingly. The desired output signal is represented by a solid and the actual by a broken line. The control variable according to equation (6) is characterized by a line with circular markers. From fig. 5 it can be seen that the random coding pattern performs better.



a)

b)

Fig 5: Results of the identification and control of a system with disturbances

## 6. Conclusions

On the basis of the obtained results the following conclusions can be drawn:

The approximation characteristics of a CMAC net depend in contrast to many other neural network types not only on the learning algorithm and the basic functions, but also on the choice of the coding pattern of information, i.e. the arrangement of the neurons in the input layer.

The choice of the distribution pattern of the associative neurons affects also the quality of control of nonlinear systems.

The coding pattern in which the neuron layers of the quantization matrices are randomly arranged has proven to be most effective.

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