Cellular Optimal Linear Associative Memories for Statistical Process Control: A Preliminary Study and Proposal

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Abstract: - The continuous detection and correction of unnatural process behaviours, due to special causes of variations, is a basic task in manufacturing to maintain any process stable and predictable. For this purpose, updated tools for Statistical Process Control have been studied so far, like the use of Artificial Neural Networks for pattern recognition in control charts. In this paper a preliminary study for the employment of Cellular Neural Networks (CNNs) for statistical process control is presented. In particular, the properties of CNNs when behaving as Optimal Linear Associative Memories in pattern recognition are analysed, with the aim of exploiting memories to recognize one or more patterns corresponding to reference behaviours on control charts. Discussion and future research trends are highlighted.

Key words: - Statistical Process Control, Cellular Neural Networks, Recognition Process, Associative Memories

1. Introduction

In manufacturing the occurrence of variability is a part of the real practice during any process. In this field the idea at the basis of continuous improvement is the constant reduction of variability, other than properly intervening to correct unnatural increases. In particular, Statistical Process Control (SPC) is one of the most assessed techniques to catch a continuous variability reduction [1-5]. In detail, SPC can be thought as consisting of several stages: observation, evaluation, diagnosis, decision and implementation. On this proposal, improving the degree of automation in one or more of these stages can be extremely useful to provide objective evidences for decision making in corrective actions. In this scenario, the need of suitable methodologies is felt to assure objective and accurate information processing from the available measurements. In this direction, in the last decade some attempts have been made by the scientific community, to address the problem of automating SPC [3]. A growing interest has been devoted both to the detection of special causes of variation and to automating control charting. In particular, the automatic pattern recognition on control charts using Artificial Neural Networks has been dealt with [6-16].

In this paper a feasibility study for investigating the potentialities of cellular neural networks when behaving as associative memories in SPC is developed [17]. The paper is organised in the following way. A literature review of applications of neural networks (NN) to SPC is firstly presented; successively, the main points to face in an automatic SPC system are discussed and the idea of the proposed approach is illustrated. Then, a theoretical explanation of the properties of optimal linear associative memories, together with the model of cellular neural networks is provided. Finally, a discussion on the proposal is reported.

2. Literature review

In the last decade the problem of pattern-recognition for control charting has been widely addressed by researchers. Topics covered can be essentially divided into two parts:

Statistical classification and heuristic methods

In [1] Guo & Dooley propose a Bayesian pattern recognition based on discriminant function techniques. Then the authors compare this approach with an EBP neural network for an univariate quality characteristic process.

In [3] a general mathematical pattern recognition algorithm to reveal any pre-specified sequence or non-random pattern on an x-bar control chart is used.

Artificial Neural Networks (ANNs)

Among the applications developed so far, in [6] Cheng uses a 3-layer fully-connected neural network to detect gradual trends and sudden changes in the process mean. Moreover, in [8] Cheng proposes both a Multi-layer Perceptron NN and a modular NN for pattern recognition in the process mean. In [9] a multi-layered NN is developed using an histogram representation method to present data.

In [10, 11] the application of radial basis function NNs is proposed for identifying shift in process parameters in the presence of autocorrelation [10] and for addressing correlated and dynamic multivariate production operation control [11]. Then, abnormal pattern recognition of control charts are analyzed in [12] using multilayered neural networks, addressing univariate quality characteristics and constant variance in [13] and mixed abnormal patterns in [14]. At last, in [15] two feed-forward multi-layered NNs are used to recognize unstable patterns in x-bar control charts.

Combined approach

In [7], Liao proposes a multi-layered neural network coupled with two learning algorithms to detect simultaneously process mean and variation, whereas in [15] Chang proposes a NN scheme with three modules to detect variance shift and its change magnitude; it consists of two multi-layered BPN and a resampling mechanism.

However, one of the most critical points when using ANNs is the data representation strategy. In reviewed literature, the following choices resulted:

- direct representation: samples of data are presented to the ANN in forms of data points vs. magnitudes [10]
- histogram representation: data points are pre-processed, by transforming measured data into frequency counts before the submission to ANNs
- *ad-hoc* coding schemes: in [6] and [8] Cheng divides the range of input data in two zones of 0.5 $\sigma_{x\text{-bar}}$ representing data by the midpoint of these zone intervals
- data standardisation coupled with a coding process: it can be faced either dividing the variable range in a fixed number of intervals to reduce the noise effect from common causes [13]; encoding decimal observation to binary format [16].

As a consequence, the following advantages and drawbacks in using ANNs for SPC come out.

Advantages

i) A better performance than traditional statistical classification methods, either in terms of Average Run Length (ARL) or in terms of Type I error (fewer false alarm signals).
ii) Flexibility, allowing the process analyst to design a desired control scheme based on a well-prepared control scheme, thus adding also other patterns.
iii) ANN seems to be satisfactory in detecting small process shifts in the process mean [6].
iv) The recall process is very fast.

Disadvantages

i) All the paper mentioned so far used supervised ANNs, relying on the basic assumption that there are well-defined patterns to detect and a sufficient number of training examples.
ii) Another critical point of all the ANN applications for SPC is the extensive demand for training processes, as well as of training data across a wide spectrum of possible change in magnitude, in order to yield satisfactory performance. To this extent, most of the applications uses Monte Carlo simulation to generate training data.
iii) There is no general rule to optimize ANN design for any situation.
iv) The signal-to-noise ratio results critical to the effectiveness of pattern recognition of ANNs.
v) The BPN has no memory abilities, which might result in a drawback for model applications in changing environments.

3. Statistical process control

At present statistical process control is one of the most commonly used tools for monitoring the variability of processes in manufacturing environment. Control charting is a well known tool of SPC, given its strong potentialities as a graphical tool to visualize the natural evolution of a process, through the representation of the behaviours of one or more measurable quality-characteristic variables. As an example, in Fig.1 two charts are reported. It can be noted that the appealing feature of control charting consists in the possibility for a line operator to perform ‘dynamically’ hypothesis testing without a specific statistical experience in the presence of uncorrelated variables.

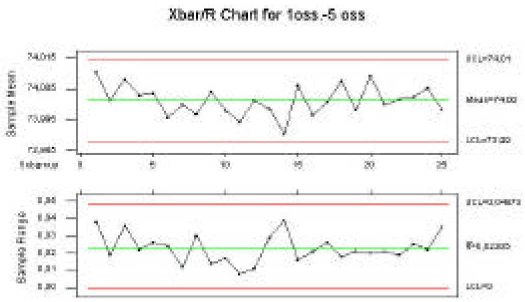

Figure 1. Example of the two most common control charts (Xbar and R)

Traditional approaches, since Shewhart scheme, have been developed over the years to improve sensitivity and effectiveness: (see, for example, pattern rules [2], CUSUM and EWMA control chart schemes [4]). ANNs have been gradually recommended as alternatives to traditional SPC techniques due to their higher performances for the following reasons:

i) classical SPC techniques do not explain actual causes of defect in the process; to diagnose types of assignable causes, more informative techniques are needed;

ii) classification of the magnitude of a specific process change, once detected, can help this diagnosis [15].

The main problem when controlling a process is to be able to rapidly and accurately predict the presence of unnatural process behaviours (i.e. the presence of special – or not assignable - causes), which result in ‘special patterns’ in the control charts, hereby summarized: 1) normal or flat (point-to-point fluctuations are unsystematic and unpredictable); 2) sloped patterns: increasing trend, decreasing trend or drift; 3) sudden upward or downward shift; 4) bimodal (stratification); 5) cycles; 6) abnormal fluctuations; 7) mixture (combination of data from different distributions) or concurrent patterns; 8) systematic variation.

Each one of these patterns could be assigned a special cause, depending on the type of monitored process. At present interpreting unnatural patterns is a challenge for quality control personnel. Problems of missing observations and incomplete observed patterns have to be taken into account in the most of real processes. Random noise and, to a certain extent, similarity among different patterns might be two serious problems in pattern recognition tasks. In fact, a common difficulty existing in operators’ trend recognition is the incorrect discrimination between similar patterns, due to the inherent common cause variation in any process [14].

As a final point to address, it should be remembered that real operating situations are characterized by more than one quality characteristics, which are neither necessarily stochastically independent nor stable in time.

4. Fundamentals of the approach

In this section the basic ideas of the proposed approach for the automatic detection of unnatural behaviours of data to maintain a tighter process control are examined. Taking into account the previously presented literature review, in so far as the authors are aware, until now Cellular Neural Networks have never been used for SPC automation purposes.

The employment of Cellular Neural Networks (CNNs) [17] for statistical process control is here thought to be extremely useful, on the basis of the following properties of CNNs when behaving as optimal linear associative memories for pattern recognition:

1) possibility of exploiting memories to recognize one or more patterns on control charts corresponding to reference behaviours for the necessary corrective actions;

2) locally connected nature of CNN architecture, which is effective for the hardware implementation of the synthesized circuits;

3) capability of performing real-time pattern recognition even in the presence of noisy or partial data.

A monitoring process is here devised involving a database, a data processing neural system and proper corrective actuators. The proposed data processing neural system could be based on the behaviour of an Optimal Linear Associative Memory (OLAM) which could realize the necessary real time matching of data by comparing detected situations and reference memorized ones.

5. Optimal Linear Associative Memories (OLAMs)

In this section m pairs of binary vectors ($\boldsymbol{x}^i$, $\boldsymbol{y}^i$) are considered, where $\boldsymbol{x}^i$ has length n and $\boldsymbol{y}^i$ has length n+1. If stored in a memory these vectors have to be associated in such a way that [19]:

$$\boldsymbol{y}^i = \boldsymbol{M}\boldsymbol{x}^i \qquad i = 1,..., m \quad (1)$$

where $\boldsymbol{M}$ is an $[(n+1)\mathrm{x}n]$-dimensional matrix which maps $\boldsymbol{x}^i$ in $\boldsymbol{y}^i$. Equation (1) can be rewritten in compact form as:

$$\boldsymbol{Y} = \boldsymbol{M}\,\boldsymbol{X} \qquad (2)$$

where $\boldsymbol{X} = [\boldsymbol{x}^1,\ldots,\boldsymbol{x}^m] \in R^{n\times m}$ and $\boldsymbol{Y} = [\boldsymbol{y}^1,\ldots,\boldsymbol{y}^m] \in R^{(n+1)\times m}$. The synthesis of an associative memory involves the determination of a matrix $\boldsymbol{M}$, constituting the linear associative memory which satisfies Eq.(2). However, a matrix $\boldsymbol{M}$**,** which exactly recalls an equilibrium point for every memory pattern, does not always exist. In most cases this drawback can be overcome by determining another matrix $\boldsymbol{M'}$**,** able to minimize the mean-squared error of forward recall:

$$\| \boldsymbol{Y} - \boldsymbol{M'}\boldsymbol{X} \| < \| \boldsymbol{Y} - \boldsymbol{M}\boldsymbol{X} \| \quad \text{for all } \boldsymbol{M} \qquad (3)$$

The matrix $\boldsymbol{M'}$ is fundamental for an optimal linear associative memory and is given by

$$\boldsymbol{M'} = \boldsymbol{Y}^+ \boldsymbol{X}^\mathrm{T} \qquad (4)$$

where $\boldsymbol{Y}^+$ is the pseudoinverse matrix of $\boldsymbol{Y}$. This associative memory is defined linear, since it satisfies the property of linearity. In fact, given two memories $\boldsymbol{y}^i = \boldsymbol{M'}\,\boldsymbol{x}^i$ and $\boldsymbol{y}^j = \boldsymbol{M'}\,\boldsymbol{x}^j$, then

$$\boldsymbol{y}^i + \boldsymbol{y}^j = \boldsymbol{M'}\,(\boldsymbol{x}^i + \boldsymbol{x}^j) \qquad (5)$$

This interesting property motivates the choice of an OLAM as a memory particularly adequate to recognize patterns using control charts and given reference behaviours. Moreover, the matrix $\boldsymbol{M'}$ reveals optimal because it is the best solution to minimize the mean-squared error of forward recall.

6. Model of Cellular Neural Networks (CNNs)

The model of an (MxN)-cell rectangular CNN can be expressed in vector form as [17]:

$$\boldsymbol{x}(k+1) = \boldsymbol{T}\,\boldsymbol{y}(k) + \boldsymbol{I} \qquad (6a)$$
$$\boldsymbol{y}(k) = \boldsymbol{g}(\boldsymbol{x}(k)) \qquad (6b)$$

where $\boldsymbol{x} = [x_1,...,x_n]^\mathrm{T} \in R^n$ is the state vector with n= MxN, $\boldsymbol{y} = [y_1,...,y_n]^\mathrm{T} \in R^n$ is the output vector, $\boldsymbol{I} = [I_1,...,I_n]^\mathrm{T} \in R^n$ contains the current sources values and $\boldsymbol{g} = [g,...,g]^\mathrm{T} \in R^n$, where the function g: $R \rightarrow R$ is a continuous, and piecewise linear output function in the form

$$g(x) = (|2x+1| - |2x+1|)/2 \qquad (7)$$

The sparse matrix $\boldsymbol{T} = [T_{ij}] \in R^{n\times n}$ is the interconnection matrix, which takes into account the local connection property of the cellular neural network architecture.

Any point $\boldsymbol{x_0} \in R^n$ is said to be an equilibrium point of (6) if [19]

$$\boldsymbol{x_0} = \boldsymbol{T}\,\boldsymbol{g}(\boldsymbol{x_0}) + \boldsymbol{I} \qquad (8)$$

Moreover, it can be proved that the suggested model assures the asymptotic stability of any equilibrium point of system (6), which is a necessary condition to generate an associative memory.

7. Discussions and future work

In this paper a preliminary study for exploiting Cellular Optimal Linear Associative Memories for statistical process control has presented. An important motivation of the present research is the almost widely known interest in intelligent manufacturing systems, due to the fact that, in such systems, a rapid interpretation of process data becomes essential. On this proposal, all the scientific work developed so far has been oriented to a software approach for SPC automation. The present paper addresses a novel point of view in this field: the possibility of integrating SPC functions from an architectural point of view, aiming at future hardware realizations of neural networks for pattern recognition on control charts.

This could potentially improve dramatically both the unmanned aspect of process control and the real-time on-line feature for which these applications are intended to.

Some critical drawbacks of other ANN applications could be potentially solved by considering cellular associative memories, namely: i) lack of memory; ii) difficulty of recognizing unnatural patterns interactions; iii) autocorrelated data treatment

This kind of neural networks seems to be promising due to their capabilities of storing reference patterns and recognizing them even in noisy cases or in emergency situations. Cellular Optimal Linear Associative Memories should be able to recover quite satisfactorily the memorized patterns also in some difficult cases. Further analysis with experimental developments are being carried out on this line.

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