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Control chart pattern recognition using an optimized neural network and efficient features

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ABSTRACT

Automatic recognition of abnormal patterns in control charts has seen increasing demands nowadays in manufacturing processes. This study investigates the design of an accurate system for control chart pattern (CCP) recognition from two aspects. First, an efficient system is introduced that includes two main modules: the feature extraction module and the classifier module. The feature extraction module uses the entropies of the wavelet packets. These are applied for the first time in this area. In the classifier module several neural networks, such as the multilayer perceptron and radial basis function, are investigated. Using an experimental study, we choose the best classifier in order to recognize the CCPs. Second, we propose a hybrid heuristic recognition system based on particle swarm optimization to improve the generalization performance of the classifier. The results obtained clearly confirm that further improvements in terms of recognition accuracy can be achieved by the proposed recognition system.

1. Introduction

Control chart patterns (CCPs) are important statistical process control tools for determining whether a process is run in its intended mode or in the presence of unnatural patterns. CCPs can exhibit six types of pattern: normal (NR), cyclic (CC), increasing trend (IT), decreasing trend (DT), upward shift (US) and downward shift (DS) [1]. All patterns other than normal patterns indicate that the process being monitored is not functioning correctly and requires adjustment.

Over the years, numerous supplementary rules known as zone tests or run tests [2] have been proposed to analyze control charts. Interpretation of the process data still remains difficult because it involves pattern recognition tasks. It often relies on the skill and experience of the quality control personnel to identify the existence of an unnatural pattern in the process. An efficient automated control chart pattern (CCP) recognition system can compensate this gap and ensure consistent and unbiased interpretation of CCPs, leading to a smaller number of false alarms and better implementation of control charts. With this aim, several approaches have been proposed for CCP recognition. Some researchers have used expert systems [2], and others have used artificial neural networks (ANNs) [3–13]. ANNs can be simply classified into two main categories: supervised ANNs and unsupervised ANNs. A literature review shows that the techniques which use multilayer perceptron (MLP) neural networks as the classifier have high performances. The advantage with a neural network is that it does not require the provision of explicit rules or templates. Rather, it learns to recognize patterns directly by being presented with typical example patterns during a training phase. Among the ANNs, the multilayer perceptron (MLP) with back-propagation learning algorithm is perhaps the most widely used neural network model, being easy to understand and easy to implement. Also some of the researchers have used fuzzy-clustering for recognition of CCPs [14]. A decision tree (DT) based classifier is also popular for the problem of CCP recognition [15].

Most the proposed techniques used the unprocessed data as the input of the CCP recognition system. The use of unprocessed CCP data has many additional problems, such as the amount of data to be processed being large. On the other hand, a feature-based approach is more flexible to deal with a complex process problem, especially when no prior information is available. If the features represent the characteristics of patterns explicitly and if their components are reproducible with the process conditions, the classifier recognition accuracy will increase [11]. Further, if the feature is amenable to reasoning, it will help in understanding how a particular decision was made, and this makes the recognition process a transparent process. Features could be obtained in various forms, including principal component analysis shape features [9,11], correlation between the input and various reference vectors [16], and statistical correlation coefficients [17].

Based on the published papers, there exist some important issues in the design of automatic CCP recognition system which, if suitably addressed, may lead to the development of more robust and efficient recognizers. One of these issues is the selection of the features. In this paper, we propose using the entropies of the

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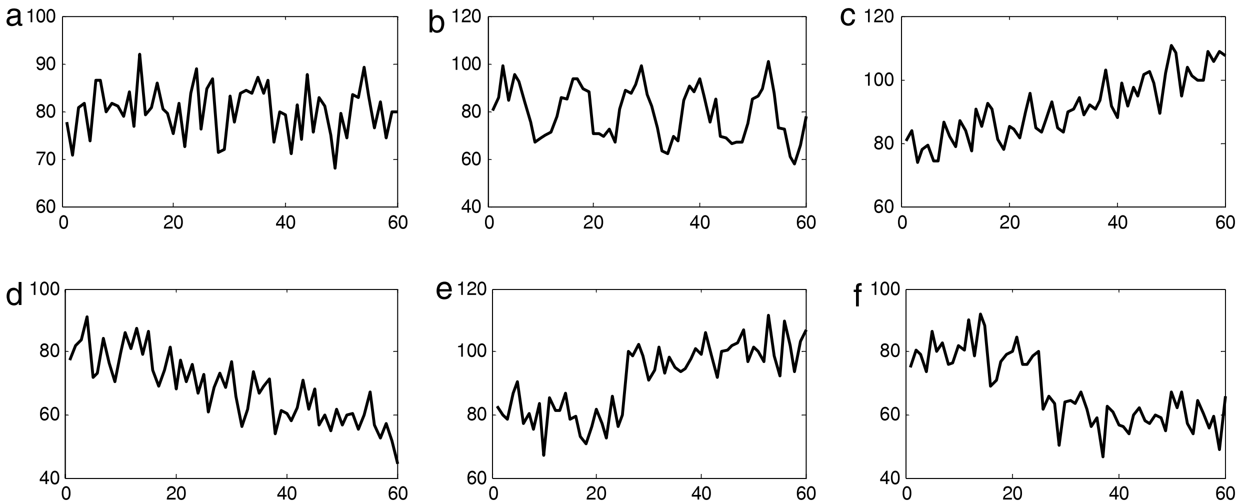

Fig. 1. Six common types of CCP: (a) Normal, (b) Cyclic, (c) Upward Trend, (d) Downward Trend, (e) Upward Shift, (f) Downward Shift. In these figures, the X-axis shows the time and the Y-axis shows the number of items that are produced.

wavelet packet decomposition as the prominent characteristics of the received pattern. These features are presented in Section 2. Another issue is related to the choice of the classification approach to be adopted. Here, in the classifier module, several neural networks, such as the multilayer perceptron and radial basis function, are investigated. Section 3 explains the classifier. Then, we propose a novel recognition system based on particle swarm optimization to improve the generalization performance of the classifier. Section 4 describes the particle swarm optimization and optimization method.

2. Feature extraction

It is most important to develop a set of features which could be used to differentiate members of the CCPs. Fig. 1 shows six pattern types of control chart.

Control chart data is non-stationary and has highly complex time–frequency characteristics. For example, trends are typically lower in frequency for a longer period of time while shifts have high frequency content for a short time.

Wavelet transformation retains the time variable information in the signal. The transformation is, instead, on scale and frequency. It allows frequency analysis and statistical analysis, with time captured in the multiple levels of decomposition [18]. However, proper choices of the wavelet family, order and decomposition level are needed to retain the signal characteristics. Based on these observations, it was decided to try a wavelet decomposition approach. The wavelet decomposition approach calls for selecting a wavelet to be used in the decomposition of the input signal [19]. Wavelet decomposition analysis produces the most effective features. Wavelet decomposition summarizes and preserves the time, frequency and phase information. This initial decomposition produces two sets of data: a set of approximation coefficients and a set of detail coefficients.

The WPD technique calls for selecting a wavelet to be used in the decomposition of the input signal. This initial decomposition produces two sets of data: a set of approximation coefficients and a set of detail coefficients. The wavelet decomposition is then applied to each of these sets to produce new sets of decompositions. This process continues for a predetermined depth. The full WPD is displayed as a tree with a discrete sequence (coefficient) at every branch. Each branch is referred to as a bin vector. Fig. 2 shows the WPD for a signal of length eight. The S in the first row represents the entire signal, with no decomposition. The second row represents the first level of decomposition. There, node A holds the approximation coefficients and D holds the detail coefficients. The third row represents the second level of decomposition, where an approximation and detail are generated for the first level approximation and an approximation and detail are generated for the first level detail. Finer granularity is produced at further levels of decomposition.

Transformation of the signal data via wavelet decomposition does not, alone, condense the amount of data that must be analyzed.

After WPD, the entropies of the wavelet packets are used as measures. The entropy function was used for characterizing each of the sets of coefficients produced by the wavelet decomposition. As we know, the confusion measurement of any data set is called the entropy. An entropy-based criterion describes information-related properties for an accurate representation of a given pattern. In this study the standard Shannon entropy function is used. The resulting values were used to form the input vector for the classifier.

3. Classifier

This section briefly describes the neural network classifiers.

3.1. Multi-layer perceptron (MLP) neural network

An MLP neural network consists of an input layer (of source nodes), one or more hidden layers (of computation nodes) and an output layer. The recognition basically consists of two phases: training and testing. In the training stage, weights are calculated according to the chosen learning algorithm. The issue of learning algorithm and its speed is very important for the MLP model. In this study the following learning algorithms are considered.

3.1.1. Back-propagation with momentum (BP with momentum)

The BP algorithm makes use of gradient descent with a momentum term to smooth out oscillation [20]. Eq. (1) gives the weight update for BP with momentum:

$$\Delta w_{ij}(t+1) = -\varepsilon \frac{\delta E}{\delta w_{ij}}(t) + \mu \frac{\delta E}{\delta w_{ij}}(t-1) \tag{1}$$

where w_{ij} represents the weight value from neuron j to neuron i, ε is the learning rate parameter, and E represents the error function. It adds an extra momentum parameter, μ, to the weight changes.