ISA Transactions 63 (2016) 256–264

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

A novel approach for recognition of control chart patterns: Type-2 fuzzy clustering optimized support vector machine ☆

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ARTICLE INFO

Article history:
Received 1 July 2014
Received in revised form
2 February 2016
Accepted 13 March 2016
Available online 18 April 2016

Keywords:
Control chart pattern
COA
Clustering
T2FCM
SVM

ABSTRACT

Unnatural patterns in the control charts can be associated with a specific set of assignable causes for process variation. Hence, pattern recognition is very useful in identifying the process problems. In this study, a multiclass SVM (SVM) based classifier is proposed because of the promising generalization capability of support vector machines. In the proposed method type-2 fuzzy *c*-means (T2FCM) clustering algorithm is used to make a SVM system more effective. The fuzzy support vector machine classifier suggested in this paper is composed of three main sub-networks: fuzzy classifier sub-network, SVM sub-network and optimization sub-network. In SVM training, the hyper-parameters plays a very important role in its recognition accuracy. Therefore, cuckoo optimization algorithm (COA) is proposed for selecting appropriate parameters of the classifier. Simulation results showed that the proposed system has very high recognition accuracy.

1. Introduction

In modern industrial and service organizations, control charts have been utilized extensively. Different kinds of control charts have been recently improved to meet higher standards and various quality characteristics with the purpose of better control. For the first time, Shewhart [1] proposed using control charts for monitoring process fluctuation in 1924. He asserted that in a process fluctuation, assignable causes make abnormal changes, while non-assignable causes lead to normal changes. Consequently, automatically recognizing control chart patterns are necessary issues to identify the process fluctuation efficiently. 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]. Except for the normal patterns, all the other patterns indicate that the process being monitored does not function correctly and requires adjustment. Fig. 1 shows six pattern types of control charts.

In recent years, several studies have been carried out for recognition of the abnormal patterns. Some of the researchers used the expert systems [2,3]. The advantage of an expert system or rule-based system is that it contains the explicit information. In an expert system, the rules can be modified and updated easily, if required. However, the probable negative aspect of deriving similar statistical properties for some pattern with different classes might raise by using rules based on statistical properties. This might lead to some problems of incorrect recognition. Artificial Neural Networks (ANNs) have also been widely applied as classifiers. ANNs can be simply categorized into two groups comprising supervised and unsupervised ANNs. Most researchers [4–6] have used supervised ANNs such as multilayer perceptron (MLP), radial basis function (RBF), and learning vector quantization (LVQ), to classify different types of CCPs. On the other hand, unsupervised methods, e.g. self-organized maps (SOM) and adaptive resonance theory (ART) have been applied to accomplish the same objectives in other studies [7,8]. One of the advantages of neural networks is their capability in handling noisy measurements which require no assumption about the statistical distribution of the monitored data. It learns to recognize patterns directly through typical example patterns during a training phase.

Although ANNs have been widely applied for detecting CCPs, they suffer from several weaknesses, such as the requirement for a large amount of training data, 'over-fitting', slow convergence velocity and relapsing into a local extremum easily [9]. The practicability of ANNs is limited due to the pre-mentioned weaknesses. Support vector machines (SVMs), based on statistical learning theory, are gaining applications in the area of pattern recognition because of their excellent generalization capability [10]. Using SVMs is the method that has received increasing attention, with remarkable results obtained recently [10]. The main difference between ANNs and SVMs is the principle of risk minimization. An

☆This paper was recommended for publication by Yang Quan Chen.

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http://dx.doi.org/10.1016/j.isatra.2016.03.004
0019-0578/

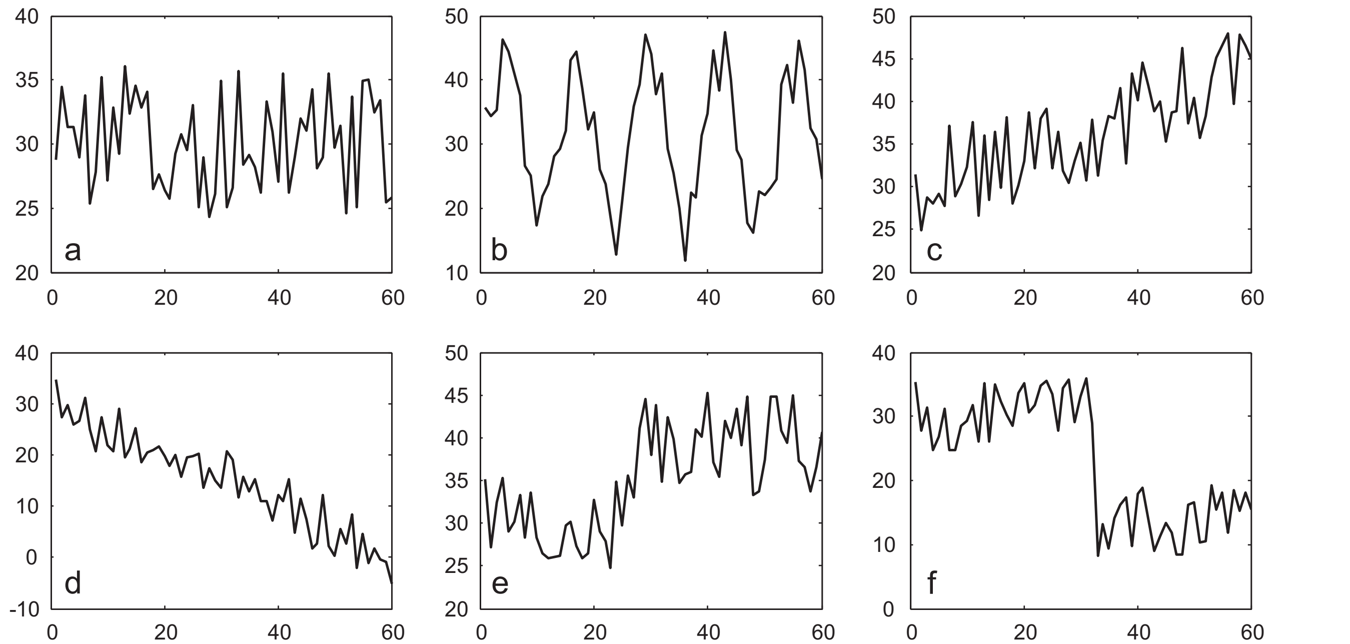

Fig. 1. Six various basic patterns of control charts: (a) normal pattern, (b) cyclic pattern, (c) upward trend, (d) downward trend, (e) upward shift, and (f) downward shift.

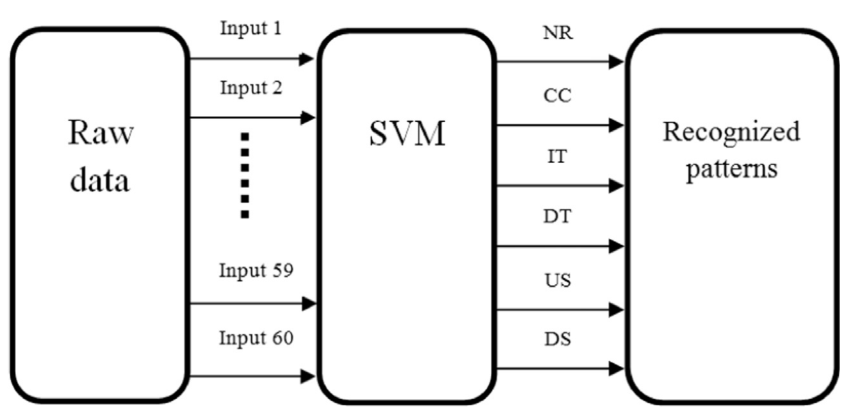

Fig. 2. Traditional SVM based CCP pattern recognition system.

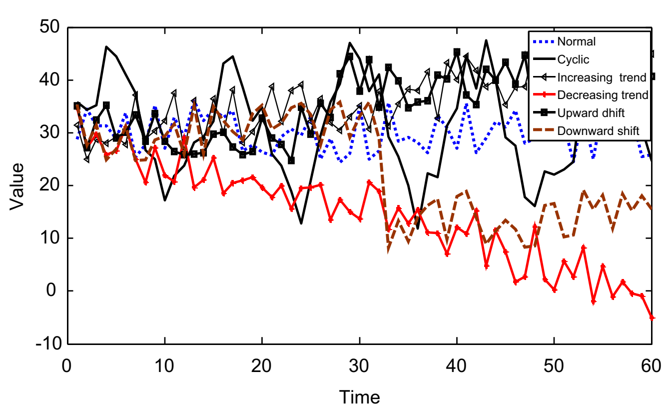

Fig. 3. Control chart patterns.

ANN implements empirical risk minimization to minimize the error on the training data, whereas an SVM implements the principle of structural risk minimization rather than experiential risk minimization, which makes it applicable in the existence of small samples [11].

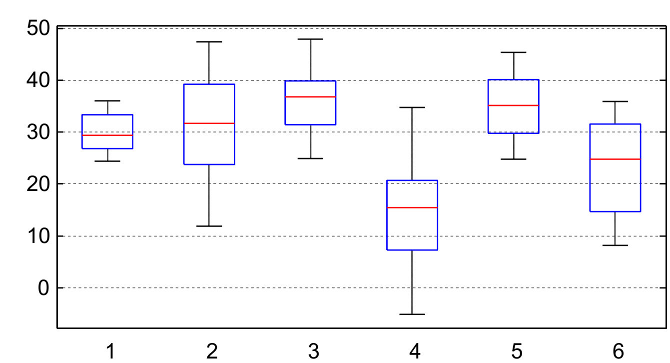

Fig. 4. Box plots of the 12 features for different classes (1=NR, 2=CC, 3=UT, 4=DT, 5=US, 6=DS).

Most of the existing techniques used the unprocessed data as the inputs of CCPs recognition system. The use of unprocessed CCP data has some problems such as the large amount of data to be processed. On the other hand, the approaches which use these features are more flexible to deal with a complex process problem, especially when no prior information is available. If the features represent the characteristics of the patterns explicitly and if their components are