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Recognition of Control Chart Patterns Using adaptive neuro-fuzzy inference system and Efficient Features

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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 process problem. This paper investigates the design of a high efficient system for recognition of common types of control chart patterns (CCPs). First it is proposed an efficient system that includes two main modules: the feature extraction module and the classifier module. In the feature extraction module, a balanced combination of the shape features and statistical features are proposed as the efficient characteristic of the patterns. In the classifier module, as the first time in this area, the adaptive neuro-fuzzy inference system (ANFIS) is investigated. Experimental results show that the proposed system has good recognition accuracy (RA). However, the results show that in ANFIS training, the vector of radius has very important role for its recognition accuracy. At the second fold, it is proposed an intelligence system which a novel optimization module, i.e., bees algorithm (BA) is proposed for finding the best parameters of the classifier. Simulation results show that the proposed system has high recognition accuracy.

Index Terms— ANFIS; Bees algorithm; Control chart patterns; Optimization; Shape features; Statistical features, Recognition, Fuzzy.

1 Introduction

STATISTICAL process control (SPC) techniques are widely used in manufacturing and other processes to monitor mean and variations in quality characteristics. SPC uses statistical signals to detect variations in the process, identify the sources of variation, improve performance and to maintain control of processes at required quality levels. Control charts, developed by Walter A. Shewhart in the 1920s, are considered as one of the most widely used SPC tools. 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. Control chart patterns (CCPs) can exhibit six types of pattern: normal (NR), cyclic (CC), upward trend (UT), downward trend (DT), upward shift (US) and downward shift (DS) [37]. Except for normal patterns, all other patterns indicate that the process being monitored is not functioning correctly and requires adjustment. Fig. 1 shows six pattern types of control chart.

In recent years, several studies have been performed for recognition of the unnatural patterns. Some of the researchers used the expert systems [16, 50]. The advantage of an expert system or rule-based system is that it contains the information explicitly. If required, the rules can be modified and updated easily. However, the use of rules based on statistical properties has the difficulty that similar statistical properties may be derived for some patterns of different classes, which may create problems of incorrect recognition. Also, ANNs have been widely applied for classifiers. ANNs can be simply categorized into two groups comprising supervised and unsupervised. Most researchers [1, 12, 13, 14, 15] have used supervised ANNs, such as multi layer perceptron (MLP), radial basis function (RBF), and learning vector quantization (LVQ), to classify different types of CCPs. Furthermore, unsupervised methods, e.g. self-organized maps (SOM) and adaptive resonance theory (ART) have been applied to fulfill the same objective in other studies [10, 11]. The advantage with neural network is that it is capable of handling noisy measurements requiring no assumption about the statistical distribution of the monitored data. It learns to recognize patterns directly through typical example patterns during a training phase. One disadvantage with neural network is the difficulty in understanding how a particular classification decision has been reached and also in determining the details of how a given pattern resembles with a particular class. In addition, there is no systematic way to select the topology and architecture of a neural network. In general, this has to be found empirically, which can be time consuming.

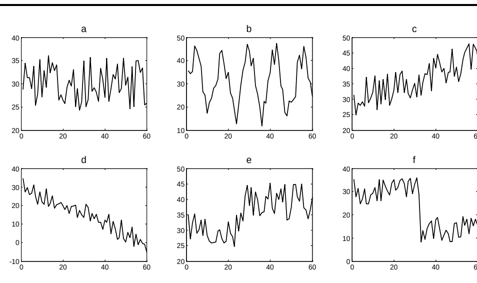

Fig. 1. Six various basic patterns of control charts: (a) Normal pattern, (b) Cyclic pattern, (c) Upward trend, and (d) Downward Trend, (e) Upward shift, (f) Downward shift

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Some of researchers have used fuzzy rules to CCPs recognition. Wang and Rowlands [56] developed a fuzzy rule based inference system based on zone rules in control charts. The input variables are the degree of membership of a point in each zone represented as fuzzy sets, and the output is the process state, mapped by eleven fuzzy If-Then rules. This approach provides improved results in terms of interpretation of data and consistency, as the numeric output from the fuzzy system indicates whether or not action should be taken, if the process is out of control. Another excellent application of fuzzy logic to control charting for individuals was developed by Tannock [54]. In this approach, two fuzzy sets namely, centered fuzzy set and random fuzzy set are used. Three typical unnatural patterns: shift, trend and cyclical patterns are examined using these two fuzzy sets. Fazel Zarandi et al. [17] use fuzzy adaptive sampling rules and fuzzy run rules to increase the sensitivity of the control charts. These approaches use fuzzy logic only in analyzing the control chart patterns to determine the process state. Diagnosing the assignable cause from the signals from the patterns has not been explored in these approaches. Hsu and Chen [29] suggested an approach using fuzzy logic and genetic algorithms to diagnose the assignable cause using the signals from unnatural patterns. The system comprises of a knowledge bank and a reasoning mechanism. The knowledge bank contains the membership functions of unnatural symptoms described by Nelson's rules and knowledge of cause-symptom relations. The fuzzy cause-symptom relation matrix is constructed with the help of a new approach called maximal similarity method (MSM). In the MSM approach, an optimization problem is formulated for constructing the fuzzy relational matrix, and genetic algorithms are used for faster search techniques. This system involves increased computational complexities due to the global search for the optimal solution for constructing the fuzzy relational matrix. In [11] a subjective fuzzy rule based fuzzy inference system is developed to resolve the uncertainties in identifying the CCPs and relating them to assignable causes. The drawback of fuzzy systems is that they do not have the ability to learn and cannot adjust themselves accordingly [32].

Most the existing techniques used the unprocessed data as the inputs of CCPs recognition system. The use of unprocessed CCP data has further many problems such as the amount of data to be processed is large. This limitation can be overcome with the use of features for representing data as demonstrated in pattern recognition applications for handwritten [60], characters [3] and grain grading [57] among others. The common motivation for using features extracted from raw data is dimensionality reduction [38], which would significantly reduce the size of the input vector. It was hypothesized that a smaller classifier size using the feature-based CCP recognizer would perform and generalize better than the raw data-based recognizer. Generalization here means the ability of a recognizer to recognize correctly a pattern it has not been trained on.

Features could be obtained in various forms, including principal component analysis shape features [19, 41], multi-resolution wavelet analysis [7, 44] and statistical features [24]. Pham and Wani [41] introduced feature based control chart pattern recognition. Nine geometric features were proposed: slope, number of mean crossings, number of least-square line crossings, cyclic membership, average slope of the line segments, slope difference, and three different measures for area. The scheme was aimed at improving the performance of the pattern recognizer by presenting a smaller input vector. Gauri and Chakraborty [19] also present a set of seven most useful features that are selected from a large number of potentially useful features using a CART based systematic approach. Based on these selected features, eight most commonly observed CCPs are recognized using heuristic and ANN techniques. Chen et al. [7] presents a hybrid approach by integrating wavelet method and neural network for on-line recognition of concurrent CCPs. In the hybrid system, concurrent CCPs are first preprocessed by a wavelet transform to decompose the concurrent patterns into different levels or patterns, and then the corresponding features are fed into back-propagation ANN classifiers for pattern recognition. Hassan et al. [24] conducted an experimental study to use BPNs for identifying six types of basic SPC patterns, where the performances of two BPN recognizers using statistical features and raw data as input feature, respectively, were compared. The results indicated that the BPN using statistical features as input vectors has better performance than those of the other BPN using raw data as input vectors.

Based on the published papers, there exist some important issues in the design of automatic CCPs recognition system which if suitably addressed, lead to the development of more efficient recognizers. One of these issues is the extraction of the features. In this paper for obtaining the compact set of features which capture the prominent characteristics of the CCPs in a relatively small number of the components, the statistical and shape features are applied. These features are presented in Section 2.

Another issue is related to the choice of the classification approach to be adopted. The developed method uses fuzzy rules for recognition task. In the proposed method, an expert system has been developed which has fuzzy rules obtained by ANFIS. ANFIS represent the promising new generation of information processing systems. Adaptive network based fuzzy inference systems are good at tasks such as pattern matching and classification, function approximation, optimization and data clustering, while traditional computers, because of their architecture, are inefficient at these tasks, especially pattern-matching tasks [5, 28, 33].

In ANFIS training process, the vector of radius has high efficiency on the performance of system. In order to increase the accuracy of proposed system, we intend to find the optimum vector of radius using the optimization algorithm. In the proposed method bees algorithm (BA) is used for finding the optimum vector of radius that it's more robust performance than other intelligent optimization methods has proved. The computational simulations reveal very encouraging results in terms of the quality of solution and the processing time required [42].

The rest of paper is organized as follows. Section 2 explains the feature extraction. Section 3 presents the classifier. Section 4 presents the optimization method. Section 5 shows some simulation results and finally Section 6 concludes the paper.

2 Feature extraction

Features represent the format of the CCPs. Different types of CCP have different properties; therefore finding the suitable features in order to identify them (especially in higher-order and/or non-square cases) is a difficult task. In the signal recognition area, choosing good features not only enables the classifier to distinguish more and higher CCPs, but also helps reduce the complexity of the classifier. In this paper, for the feature extraction module we have used a suitable set of features that consists of both shaping and statistical information of the CCPs. This section briefly describes these features.

2.1 Shape features

The shape features used by the CCP recognizer in this study are such that they facilitate recognition of CCPs quickly and accurately. The six types of CCP considered in this work have different forms, which can be characterized by a number of shape features. In [41], the authors have introduced nine shape features for discrimination of the CCPs. In this paper, based on trial and error, eight of these features are considered. These features have been chosen such that they and the proposed statistical features can significantly recognize the patterns quickly and accurately. These features are as follows.

(1) S: the slope of the least-square line representing the pattern. The magnitude of S of this line for normal and cyclic patterns is approximately zero, while that for trend and shift patterns is greater than zero. Therefore S may be a good candidate to differentiate natural and cyclic patterns from trend and shift patterns.

(2) NC1: the number of mean crossings, i.e. the crossings of the pattern with the mean line. NC1 is small for shift and trend patterns. It is highest for normal patterns. For cyclic patterns, the number of crossings is intermediate between those for normal patterns and shift or trend patterns. This feature differentiates normal patterns from cyclic patterns. It also differentiates normal and cyclic patterns from trend and shift patterns.

(3) NC2: the number of least-square line crossings. NC2 is highest for normal and trend patterns and lowest for shift and cyclic patterns. Thus it can be used for separation of natural and trend patterns from others.

(4) AS: the average slope of the line segments. In addition to the least-square line which approximates the complete pattern, each pattern also has two line segments which fit the data starting from either end of the pattern. The average slope of the line segments for a trend pattern will be higher than for normal, cyclic and shift patterns. This feature therefore differentiates trend patterns from other patterns.

(5) SD: the slope difference between the least-square line and the line segments representing a pattern. The SD value is obtained by subtracting the average slope as of the two line segments from the slopes of the least-square line. For normal, cyclic and trend patterns, the least-square line and the line segments will be different. Thus, the SD will have a high value for a shift pattern and small values for normal, cyclic and trend patterns. This feature therefore differentiates a shift pattern from other patterns.

(6) APML: the area between the pattern and the mean line. The APML is lowest for a normal pattern. Thus, this feature differentiates between normal and other patterns.

(7) APSL: the area between the pattern and its least-square line. Cyclic and shift patterns have a higher APSL value than normal and trend patterns and therefore the APSL can be used to differentiate cyclic and shift patterns from normal and trend patterns.

(8) ASS: the area between the least-square line and the line segments. The value of this feature is approximately zero for a trend pattern and is higher for a shift pattern. This feature thus differentiates trend patterns from shift patterns.

2.2 Statistical features

Some statistical features are mean, standard deviation, skewness, kurtosis, and autocorrelation. The value of mean is approximately equal for a normal and cyclic pattern and is different for remaining patterns. This feature thus differentiates normal and cyclic patterns from other patterns

The value of standard for a normal pattern will be lower than other patterns. This feature therefore differentiates normal pattern from other patterns. Skewness provides the information regarding to the degree of asymmetry and kurtosis measures the relative peakness or flatness of its distribution [24]. Their mathematical forms are respectively shown below:

$$mean = \frac{\sum_{i=1}^{n} X_i}{n} \tag{1}$$

$$std = \sqrt{\frac{\sum_{i=1}^{n} (X_i - mean)^2}{n}} \tag{2}$$

$$skew = \frac{\sum_{i=1}^{n} (X_i - mean)^3}{n} \tag{3}$$

$$kurt = \frac{\sum_{i=1}^{n} (X_i - mean)^4}{n} \tag{4}$$

Figure 2 shows these twelve features for each class. It can be found that the patterns related to the different classes can be separated within the feature space.

3 Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS represents a useful neural network approach for the solution of function approximation problems. Data driven procedures for the synthesis of ANFIS networks are typically based on clustering a training set of numerical samples of the unknown function to be approximated. Since introduction, ANFIS networks have been successfully applied to classification tasks, rule-based process controls, pattern recognition problems and the like. Here a fuzzy inference system comprises of the fuzzy model [49, 51] proposed by Takagi, Sugeno and

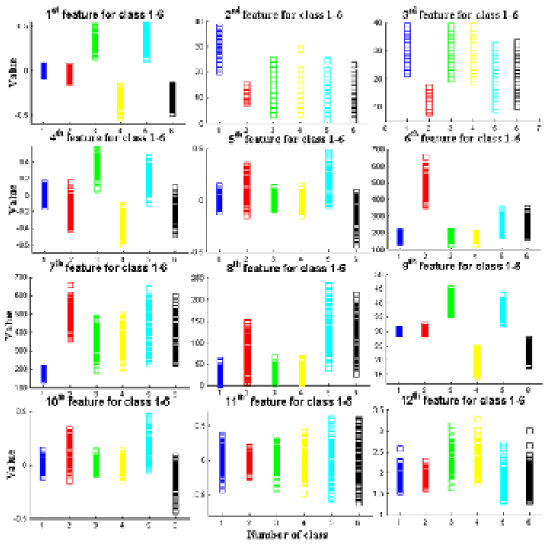

Fig. 2. Box plots of the twelve features for different classes (1=NR, 2= CC, 3=UT, 4=DT, 5=US, 6=DS). For more information see the text. First (1th) features is S, the slope of the least-square line representing the pattern. Second (2nd) feature is ,NC1, the number of mean crossings, i.e. the crossings of the pattern with the mean line. 3rd feature is NC2, the number of least-square line crossings. Fourth feature is AS, the average slope of the line segments. 5th feature is SD, the slope difference between the least-square line and the line segments representing a pattern. The sixth feature is APML, the area between the pattern and the mean line. Seventh feature is APSL, the area between the pattern and its least-square line. The eighth feature is ASS, the area between the least-square line and the line segments. The 9th , 10th , 11th and 12th features are mean, standard deviation, skewness and kurtosis respectively.

Kang to formalize a systematic approach to generate fuzzy rules from an input output data set. More details regarding ANFIS can be found in [34- 60].

4 Optimization of the Recognizer

In this study we have used BA for evolution of recognizer. This section describes this optimization technique.

4.1 bees algorithm (BA)

Bees Algorithm is an optimization algorithm inspired by the natural foraging behavior of honey bees to find the optimal solution. Fig. 3 shows the pseudo code for the algorithm in its simplest form. The algorithm requires a number of parameters to be set, namely: number of scout bees (n), number of sites selected out of n visited sites (m), number of best sites out of m selected sites (e), number of bees recruited for best e sites (nep), number of bees recruited for the other (m-e) selected sites (nsp), initial size of patches (ngh) which includes site and its neighborhood and stopping criterion. The algorithm starts with the n scout bees being placed randomly in the search space. The fitnesses of the sites visited by the scout bees are evaluated in step 2.

```
1. Initialise the solution population.
2. Evaluate the fitness of the population.
3. While (stopping criterion is not met)
//Forming new population.
4. Select sites for neighbourhood search.
5. Recruit bees for selected sites (more bees for
the best e sites) and evaluate fitnesses.
6. Select the fittest bee from each site.
7. Assign remaining bees to search randomly and
evaluate their fitnesses.
8. End While
```

Fig. 3: Pseudo code

In step 4, bees that have the highest fitnesses are chosen as “selected bees” and sites visited by them are chosen for neighborhood search. Then, in steps 5 and 6, the algorithm conducts searches in the neighborhood of the selected sites, assigning more bees to search near to the best e sites. The bees can be chosen directly according to the fitnesses associated with the sites they are visiting. Alternatively, the fitness values are used to determine the probability of the bees being selected. Searches in the neighborhood of the best e sites which represent more promising solutions are made more detailed by recruiting more bees to follow them than the other selected bees. Together with scouting, this differential recruitment is a key operation of the Bees Algorithm.

However, in step 6, for each patch only the bee with the highest fitness will be selected to form the next bee population. In nature, there is no such a restriction. This restriction is introduced here to reduce the number of points to be explored. In step 7, the remaining bees in the population are assigned randomly around the search space scouting for new potential solutions. These steps are repeated until a stopping criterion is met. At the end of each iteration, the colony will have two parts to its new population representatives from each selected patch and other scout bees assigned to conduct random searches [42].

4.2 BA-ANFIS

The ANFIS model was developed using MATLAB Fuzzy Logic Toolbox (2014). A subtractive fuzzy clustering was generated to establish a rule base relationship between the input and output parameters. The data was divided into groups called as clusters using the subtractive clustering method to generate fuzzy inference system. In this study, the Sugeno-type fuzzy inference system was implemented to obtain a concise representation of a system’s behavior with a minimum number of rules. The linear least square estimation was used to determine each rule’s consequent equation. A radius value was given in the MATLAB program to specify the cluster center’s range of influence to all data dimensions of both input and output. If the cluster radius was specified a small number, then there will be many small clusters in the data that results in many rules. In contrast, specifying a large cluster radius will yield a few large clusters in the data resulting in fewer rules [28]. For example, if the data dimension is 3 (e.g., input has two columns and output has one column), radii = [0.5 0.4

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0.3] specifies that the ranges of influence in the first, second, and third data dimensions (i.e., the first column of input, the second column of input, and the column of output) are 0.5, 0.4, and 0.3 times the width of the data space, respectively.
Therefore in this study BA-ANFIS is proposed to find the optimum vector of radius. Fig. 4 shows a sample bee. In this figure p denotes the number of input-output variables.

$$bee = [radius_1, radius_2, ..., radius_p]$$

Fig. 4. Sample of bee

Based on the above descriptions, the flowchart of the BA-ANFIS algorithm used in this paper is shown in Fig. 5. Detailed description of each step is given below:
Step 1: Unprocessed data
For this purpose we have used the practical and real world data [42].
Step 2: Feature extraction
For this purpose we have used the both shape and statistical features.
Step 3: Determine the optimum vector of radius
For this purpose BA was used as optimization algorithm and recognition accuracy (RA) is used as fitness function.
3-1: Initialization
Randomly generate a position for each candidate in [0, 1].
3.2. Fitness evaluation
3-3: Local search
3-4: Global bests
3-5: Check the termination criteria
If the termination condition is not satisfied, go to step 3-2, otherwise stop the algorithm.

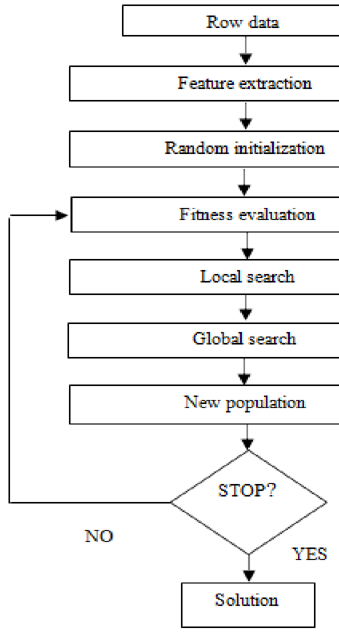

Fig. 5. Flowchart of the proposed method

5 Simulation Results

In this section we evaluate the performance of proposed recognizer. For this purpose we have used the practical and real world data [30]. This dataset contains 600 examples of control charts. In order to compare the performance of classifiers, the k-fold cross validation technique is used. The k-fold cross validation technique proposed by salzberg [47] was employed in the experiments, with k=2. The data set was thus split into two portions, with each part of the data sharing the same proportion of each class of data. One data portion were used in the training process, while the remaining part was used in the testing process. The ANFIS training methods were run two times to allow each slice of the data to take turn as a testing data. The classification accuracy rate is calculated by summing the individual accuracy rate for each run of testing, and then dividing of the total by two. All the obtained results are the average of 50 independent runs.

5.1 Performance without optimization

First we have evaluated the performance of the recognizer without optimization. Table 1 shows the RA of different systems. From Table 1 it can be seen that ANFIS with unprocessed data achieves 95.75% recognition accuracy. Its performance increases with using proposed features value up to 97.48%.

Table 1
Recognition accuracy of the recognizer without optimization

Input	Recognition accuracy (%)		
	Mean	Min	Max
Unprocessed data	95.75	94.33	96.33
Proposed features	97.48	96.00	97.66

5.2 Performance with optimization

Next, we apply BA to find the optimum vector of radius. The parameters of the bees algorithm used in this study are shown in Table 2. These values were selected for the best performance after several experiments. Table 3 compares the performance of (BA-ANFIS) model using row data and that using the proposed features. Combining the BA with the ANFIS (BA-ANFIS), we demonstrate a significantly improved performance relative to the stand-alone ANFIS model. The highest recognition accuracy (99.66%) is achieved with only 10 fuzzy rules. The reduction in the number of features also contributes in the reduction of fuzzy rules in the developed fuzzy model from approximately 360 rules to 10 rules (see Figs. 6 and 7); this contributes to reducing the computational complexity of the overall system.

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TABLE 2

PARAMETERS USED IN THE CLUSTERING ALGORITHM

Number of scout bees, *n*	20
Number of sites selected for neighborhood search, *m*	8
Number of best "elite" sites out of *m* selected sites, *e*	4
Number of bees recruited for best *e* sites, *nep*	4
Number of bees recruited for the other (*m-e*) selected sites, *nsp*	4
Number of iterations, *R*	100

TABLE 3

RECOGNITION ACCURACY OF THE RECOGNIZER WITH OPTIMIZATION

Input	Recognition accuracy (%)		
	Mean	Min	Max
Unprocessed data	96.43	95.66	97.33
Proposed features	**99.66**	**99.66**	**99.66**

Fig. 6. Fuzzy rules to identify the type of CCP using the row data

5.3 Confusion matrix

In order to indicate the details of the recognition for each pattern, the confusion matrix of the recognizer is shown by Table 4. The values in the diagonal of confusion matrix show the correct performance of recognizer for each pattern. In other words, these value show that how many of considered pattern are recognized correctly by the system. The other values show the mistakes of system. For example, look at the third row of this matrix. The value of 99.00% shows the percentage of correct recognition of upward trend pattern and the value of 1.00% shows that this type of pattern is wrongly recognized with upward shift pattern. In order to achieve the recognition accuracy (RA) of system, it is needed to compute the average value of that appears in diagonal.

TABLE 4

CONFUSION MATRIX FOR BEST RESULT (99.66%)

	NR	CC	UT	DT	US	DS
NR	100	0	0	0	0	0
CC	0	100	0	0	0	0
UT	0	0	99	0	1	0
DT	0	0	0	99.00	0	1
US	0	0	0	0	100	0
DS	0	0	0	0	0	100

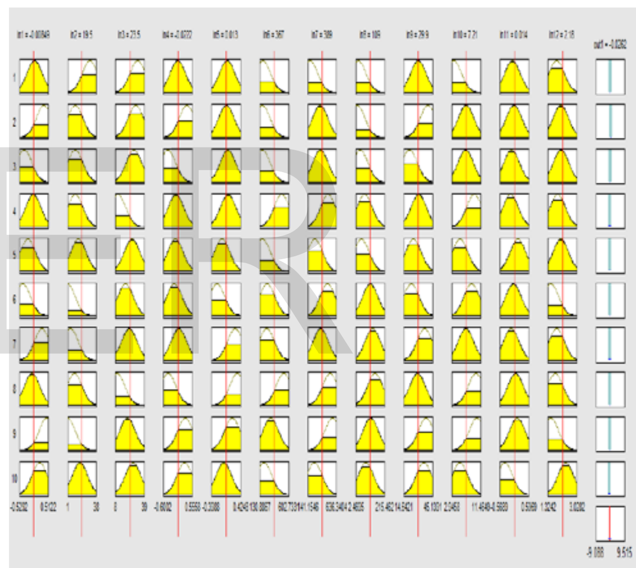

Fig. 7. Fuzzy rules to identify the type of CCP using the proposed 12 features

5.4. Performance evaluation with optimization in different runs

In this sub-section, for evaluating the performance of the BA, five different runs have been performed. Fig. 8 shows a typical increase of the fitness (classification accuracy) of the best individual fitness of the population obtained from proposed system for different runs. As indicated in this figure, its fitness curves gradually improved from iteration 0 to 100, and exhibited no significant improvements after iteration 40 for the five different runs. The optimal stopping iteration to get the highest validation accuracy for the five different runs was around iteration 30–40.

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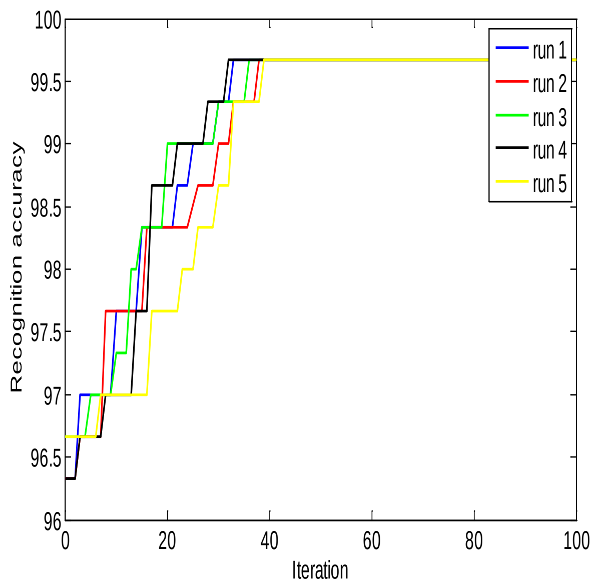

Fig. 8. Evolution of recognition accuracy for different runs

In order to compare the performance of bees algorithm (BA) with another nature inspired algorithms, we have used several nature inspired algorithms such as genetic algorithm (GA) [53], imperialist competitive algorithm (ICA) [4] and particle swarm optimization (PSO) [34] to evolve the ANFIS. Table 5 shows the obtained results. It can be seen that the success rates of BA-ANFIS is higher than the performance of other systems.

TABLE 5

COMPARISON AMONG THE PERFORMANCE OF GA-ANFIS, ICA-ANFIS, PSO-ANFIS AND BA-ANFIS.

Classifier	Recognition accuracy (%)
GA-ANFIS	98.89
ICA-ANFIS	99.16
PSO-ANFIS	99.37
BA- ANFIS	**99.66**

5.5. Comparison among the different features

As already stated the features play a vital role in classification of digital signal types. In order to investigate the effectiveness of the selected features, we have used the features that have been introduced in some references. Table 6 shows this comparison. Other simulations setup is the same. Results imply that the proposed features have effective properties in control chart patterns representation.

5.6. Comparison with different classifier

The performance of the proposed classifier has been compared with other classifiers for investigating the capability of the pro- posed classifier, as indicated in Table 6. In this respect, probabilistic neural networks (PNN) [49], radial basis function neural network (RBFNN) [43] and Multilayered perceptron (MLP) neural network with different training algorithm such as: Back propagation (BP) learning algorithm [27] and with Resilient propagation (RP) learning algorithm [45] are considered. They comprise parameters which should be readjusted in any new classification. Furthermore, those parameters regulate the classifiers to be best fitted in for classification task. In most cases, there is no classical method for obtaining the values of them and therefore, they are experimentally specified through try and error. It can be seen from Table 6 that the proposed method has better recognition accuracy than other classifiers.

TABLE 6

COMPARISON AMONG THE PROPOSED FEATURES AND SOME THE FEATURES THAT HAVE INTRODUCED IN OTHER REFERENCES.

Ref. no	Feature	RA (%)
[24]	Statistical feature	97.64
[2]	Correlation between the input and various reference	97.17
[58]	Vectors statistical correlation coefficients	98.42
[22]	Shape features	99.27
[56]	Wavelet features	99.34
This study	**Shape and statistical features**	**99.66**

TABLE 7

COMPARISON THE PERFORMANCE OF PROPOSED CLASSIFIER (BA-ANFIS) WITH OTHER CLASSIFIERS.

Classifier	Recognition accuracy (%)
PNN	91.45
RBF	97.84
MLP (BP)	90.74
MLP (RP)	97.32
BA-ANFIS	**99.66**

5.7. Comparison and discussion

For comparison purposes, Table 8 gives the classification accuracies of our method and previous methods applied to the same database. As can be seen from the results, proposed method obtains excellent classification accuracy.

TABLE 8

A SUMMARY OF DIFFERENT CLASSIFICATION ALGORITHMS TOGETHER WITH THEIR REPORTED RESULTS USED MEASURES OF THE ACCURACY

REF. NO	CLASSIFIER	RA (%)
[39]	MLP	94.30
[46]	MLP	93.73
[40]	LVQ	97.70
[41]	MLP	99.00
[21]	MLP(SPA)	96.38
[24]	MLP	97.18
[18]	MLP	97.20
[35]	MLP(RSFM)	97.46
[8]	PNN	95.58
[20]	MLP	97.22
[12]	RBF	99.60
[11]	SVM	99.37
THIS WORK	ANFIS	99.66

6 CONCLUSION

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. In this paper, we proposed a method for CCP classification based on shape and statistical features and adaptive neuro-fuzzy inference system. This paper focuses on the improvement of the classical ANFIS model by means of the integration of BA and ANFIS. Based on the experimented results, this paper recommends the use of proposed system (BA-ANFIS) for control chart recognition. The complexity of the recognition system is very low in comparison with other works. The highest level of accuracy obtained by ANFIS using unprocessed data was 95.75%. The proposed method improves the accuracy up to 97.48% by using shape and statistical features as the classifier inputs. Furthermore, optimizing the structure of the ANFIS and using shape and statistical features as the input of optimized classifier (BA-ANFIS) significantly, improves the accuracy of the proposed system up to 99.66%. The highest recognition accuracy (99.66%) is achieved with only 10 fuzzy rules.

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