Control Chart Pattern Recognition: A Comparison between Statistical Correlation Measure and Support Vector Machine (SVM)

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Abstract

Control charts are widely used in manufacturing to monitor whether a process is in control to ensure the consistency of the process. However, on emergence of any unexpected occurrence in a process, a control chart is unable to recognize the pattern of the dataset. Over the years, different methods have been developed to recognize unnatural control chart patterns. A methodology for recognizing control chart patterns is statistical correlation measure that measures correlation between a test dataset and a reference dataset. Support vector machine (SVM) has been the most popular model in recent years to recognize control chart patterns. However, computational effort in SVM model is high and training process of the model is complex and expensive. In this paper, these two methodologies have been applied to different datasets to recognize unnatural patterns. Their performance have been measured and compared. The comparison shows that SVM model performs substantially better than statistical correlation method in terms of accuracy in the output. Statistical correlation model is less expensive and associated with a simpler algorithm than the SVM model, but not as accurate as SVM model. On the other hand, the computational time required for SVM model is higher than the statistical correlation model.

Keywords
Support Vector Machine (SVM), Statistical Correlation Coefficient, Control Chart Pattern Recognition.

1. Introduction
With the ever increasing demand for various consumer products, it has become a big concern for the manufacturer to maintain the quality of their products to some extent to sustain in the competitive market environment. As a result, quality control has become an integral part of production process. For most of the cases, statistical process control is used to ensure the quality of products. Among all the statistical process control tools, control charts are considered to be the most useful tool to detect abnormal process behavior. It was first developed by Shewhart (1931). Control charts typically have a central line representing mean value and two extreme control limit lines representing the specification of a product.

Control charts are used to get important information of a process including whether a process is in control or out of control. However, if a process deviates from its normal pattern and follows a different abnormal pattern, it is not possible for a control chart to detect them, since, control charts don't provide any pattern related information. Control charts are only concerned with the last point plotted in the chart rather than the trend of points.
However, recognition of control chart patterns (CCPs) are important since a fluctuation involves abnormal changes and normal changes due to assignable causes. After a long period of research and reviews, CCPs are mostly classified into normal patterns (NOR) and six types of abnormal patterns (Yang & Yang 2005). All of them provide occurrence

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of unnatural patterns. Different techniques regarding control chart pattern recognition have been developed through the years by extensive research. One of the most traditional techniques is using statistical correlation co-efficient method. In this method, an important issue is to select the threshold value and pattern length of the test data. There are other approaches like artificial intelligence techniques which are used for control chart pattern recognitions. At present, Support Vector Machine (SVM) is very popular for control chart pattern recognitions. SVM is a learning model with associative learning algorithm which analyzes data for classification.

1.1. Control Charts

Statistical process control chart or control charts are the representation of a process in the form of a graph. It shows how a process changes over time. Control charts are used to routinely monitor quality of a process. Typically, a single quality characteristics is calculated and plotted in the control chart with respect to the sample number or time.
Generally, the chart consists of a center line that represents the mean value for the in-control process. Other two horizontal lines are called the upper control limit (UCL) and the lower control limit (LCL). A process is in-control when almost all of the data points fall within these limits.

1.2. Control Chart Patterns

Over the years, several unnatural patterns of control chart have been reported in real industrial problems. Each of them reflects different faults in mechanism. CCPs are mainly classified into normal patterns (NOR) which is shown in figure 1 and six types of abnormal patterns including Up Shift (US), Down Shift (DS), Up Trend (UT), Down Trend (DT), Up Trend (UT), Cyclic (CYC), Systemic (SYS) (Yang & Yang. 2005). All of them provide occurrence of unnatural behavior in a process. All of these patterns can be generalized as:

Normal Pattern: In a normal pattern, the data points follow a standard normal curve pattern. Most of the points are distributed nearly the average value. A few points can approach the control limits. It is very rare that a point will exceed the control limit in a normal pattern. Figure 1 shows a typical normal pattern.
Trend patterns: A continuous movement in the positive or negative direction causes trend patterns. There are two types of trend patterns; upward trend and downward trend. Tool wear, equipment depreciation can cause trend pattern in production. Figure 4 and 5 shows the upward and downward trend patterns respectively.
Shift patterns: Shift pattern can be defined as a sudden change above or below the process mean value. There might be upward shift or downward shift. Alteration in process, change of raw materials causing shift are some of the reasons for which shift pattern can take place in control charts. Figure 2 and 3 represents upward and downward shift patterns respectively.
Cyclic patterns: In cyclic patterns peaks are always followed by throughs in a periodic manner. Incidents like periodic rotations of operators are responsible for causing cyclic deviation are responsible for causing cyclic pattern. Figure 6 shows this pattern.
Systematic patterns: A point-to-point fluctuation can be occurred systematically in a systematic pattern. A low point is always followed by a high point in systematic patterns. Figure 7 illustrates this pattern.
The rest of the paper is arranged as follows. Section 2 covers the literature reviews. In section 3, methodologies of statistical correlation measure and SVM are described. Section 4 shows the numerical illustrations of the methodologies and comparison between two methods. Lastly section 5 covers conclusion and future works.

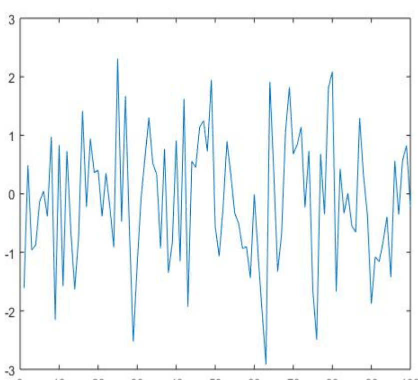

Figure 1. Normal pattern

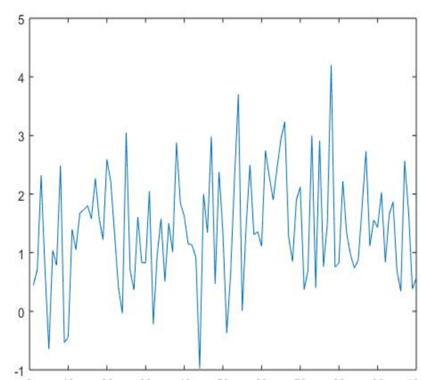

Figure 2. Upward shift pattern

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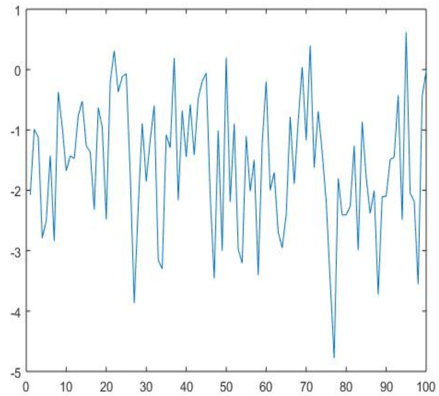

Figure 3. Downward shift pattern

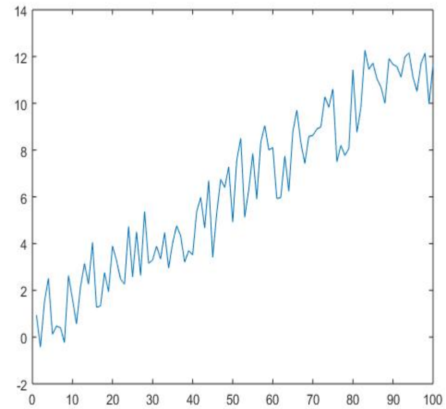

Figure 4. Upward trend pattern

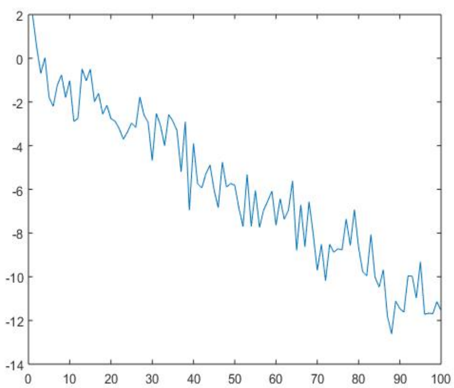

Figure 5. Downward trend pattern

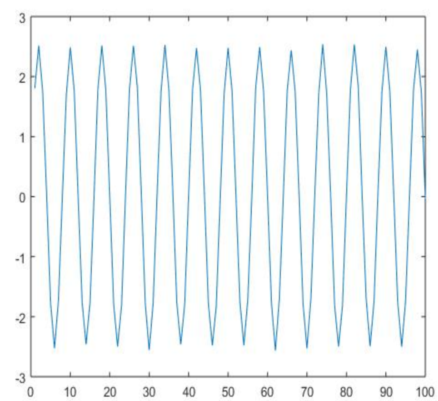

Figure 6. Cyclic pattern

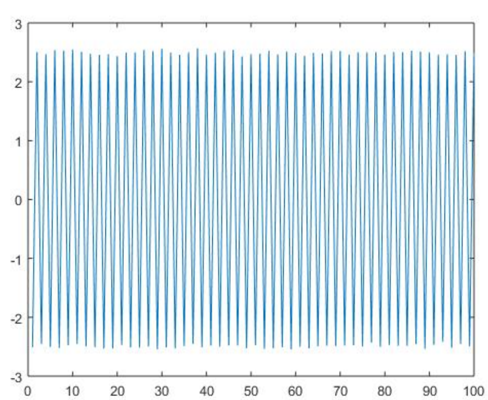

Figure 7. Systematic pattern

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2. Background Literature

Over the years, there have been many studies and research to develop different techniques for control chart pattern (CCPs) recognition. Hwarng and Hubele (1993) used a back-propagation neural network technique to detect X-bar control charts. Pham & Oztemel (1994) used learning vector quantization networks for control chart pattern recognition. Neural network approach to recognize unnatural pattern was used by Cheng (1997) and Guh and Hsieh (1999). Guh and Tannock (1999) used a back-propagation (BPN) network learning to perform this recognition task. Although backpropagation network has a good network construction leading to a good learning structure, the approach is slow and complicated.

Yang and Yang (2005) used a simple mechanism to recognize these unnatural patterns. In their paper, the statistical correlation coefficient approach was used to construct a control chart pattern recognition system. By adding a threshold criterion, these unnatural patterns were recognized, even though they changed from normal to abnormal at any point in control charts. Selection of a threshold and pattern length were a big problem in this approach.

Support vector machine has been the most popular pattern recognition technique over the years and there have been many studies to recognize control chart patterns using SVM over last few years. Support vector machines cast as derivatives of the statistical learning theory, proposed by Cortes and Vapnik (1995). Being different from NNs (neural networks), SVMs can control more effectively and no local minimum exists. Thus, they perform well in many applications, such as classification, regression, distribution estimation and so on. Huang and Wang (2006) proposed GA-based feature selection and parameters' optimization for support vector machines. Hsu and Lin (2002) published a comparison of methods between one-against-one and one-against all SVMs. Wang et al (2007) proposed multiclass support vector machine (MSVMs) model for control chart pattern recognition. There are two categories of approaches for MSVMs. One of them involves constructing and combing several binary classifiers, the other one involves directly considering all the data in one optimization formulation. The one-versus-one method is better than one-versus-rest method, because it is easy to understand, it has similar accuracy with a higher training speed. Shao (2012) developed a model for recognizing control chart patterns using decision tree of multiclass SVM. Zhao et al. (2017) published a paper on recognition of control chart pattern using improved supervised locally linear embedding and support vector machine. Wu et al. (2015) proposed control chart pattern recognition using an integrated model based on binary-tree support vector machine. A weighted support vector machine method for control chart pattern recognition was proposed by Xanthopoulos and Razzaghi (2014) and Ranaee et al (2010) proposed the application of the PSO–SVM model for recognition of control chart patterns.

Both the statistical correlation and SVM have been separately used in many research works for recognizing different types of control chart patterns but the comparison of their accuracy has not yet been done. Here in this paper, recognition of control chart patterns has been performed with both the methods and after that their accuracy is compared.

3. Methodology

In this paper, two different pattern recognition techniques are used to detect unnatural control chart patterns and results obtained from the techniques are compared with each other to recommend the best technique in order to get accurate outcomes.

3.1. CCPR using statistical correlation coefficient method

The statistical correlation measures linear relation between two datasets. Let *x* and *y* be two random vectors where $\bar{x}$ and $\bar{y}$ are the mean of the two vectors respectively. This correlation (*r*) between these two random vectors *x* and *y* is defined as:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}} \tag{1}$$

Before recognition, a training algorithm has to be implemented to get *N* samples where each pattern sample has a length of *n*. Different pattern samples can be generated by using Eq. (2-6) where *x(t)* is the randomly generated vector using different formulas.

Normal Pattern: Normal pattern are generated using Eq. (2):

$$x(t) = n(t) \tag{2}$$

where *n(t)* follows a normal distribution *N (0,1)*.

Upward and downward shift patterns: Upward and downward patterns can be described as in Eq. (3):

$$x(t) = n(t) \pm ud \tag{3}$$

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where d is the shift quantity and value of $u = 0$ before shifting and $u = 1$ after shifting. Using plus sign in Eq. (3), upward shift patterns can be generated and using negative sign downward shift patterns are generated.

Upward and downward trend patterns: Upward and downward trend patterns are described in Eq. (4):

$$x(t) = n(t) \pm dt \tag{4}$$

where d is the value of slope of the trend. Using plus sign in Eq. (4), upward trend patterns can be generated and using negative sign downward trend patterns are generated.

Cyclic pattern: Cyclic pattern is shown in Eq. (5):

$$x(t) = n(t) + d\ \sin(\frac{2\pi t}{8}) \tag{5}$$

where d is the value of amplitude.

Systematic pattern: Systematic pattern can be defined as in Eq. (6):

$$x(t) = n(t) + (-1)^t d \tag{6}$$

where d is the value of amplitude.

A training algorithm is necessary to generate each pattern. The following steps are followed for each pattern:

- A pattern length of n has to be determined.
- Using a disturbance level of d, a pattern sample generator is selected. A pattern vector $\boldsymbol{x_1}$ is generated for a pattern length of n. Accordingly $\boldsymbol{x_2}, \boldsymbol{x_3}$….., $\boldsymbol{x_N}$ pattern vectors are generated.
- From N samples a reference pattern vector $E(x)$ will be determined by
  $$E(x) = \frac{\sum_{i=1}^{N} x_i}{N}$$

For classification of patterns, a classification algorithm is followed. The steps for classification algorithm are:

- Determining a threshold value h.
- A processing data sequence containing recent n points is considered to be the pattern size to be recognized.
- Input data are tested and statistical correlation coefficients are calculated using Eq. (1) for all of the six types of generated data pattern.
- Maximum value of correlation coefficient is chosen among all outputs to determine the pattern of input data. If maximum value is smaller than threshold h, pattern is then classified as normal pattern.

3.2. CCPR using Support Vector Machine

Support Vector Machine (SVM) is a popular learning algorithm which is widely used in categorization and classification problems. It was originally designed to solve binary classification problems but it can also be used for solving multi-class problems. To solve non-linear problems using SVM, it uses Kernel Trick. The main idea behind kernel trick is to map the original data points into a higher dimensional feature space in which they can be separated by a linear classifier. The projection of this linear classifier in higher dimensional feature space is a non-linear one in the original feature space.

Binary SVM: An SVM model mainly solves a classification problem by constructing an optimal separating hyperplane between two different classes of data. The optimal separating hyperplane (OSH) maximizes the margin between the two nearest data points belonging to two separate classes.

If the training set is $(x_i, y_i), i = 1, 2, \dots\dots, l,\ x \in R^d, y \in \{-1, +1\}$, this data set can be separated by the hyperplane $w^T x + b = 0$, where w is the weight vector and b is the bias. The SVM classifies the data points by identifying a separating hyperplane whose distance is maximum with respect to the data points of each class. The separation hyperplane defined by the parameters w and b can be obtained by solving the Convex optimization problem as shown in Eq. (7) below-

$$\min \frac{1}{2}\ ||w^2|| \tag{7}$$

subject to $y_i(w^T \emptyset(x_i) + b) \geq 1\ i = 1,2, \dots .l$

where $\emptyset$ is the kernel function.

Multiclass SVM: Binary SVM problem can be extended to multi-class SVM problem in two widely used methods. One of them is called the one-against-all (OAA) method. OAA involves training a single classifier per class with samples of that class as positive samples and all other samples as negative. Here, a sample is given as input to all the SVMs. If this sample belongs to classP_I; only the SVM trained to separate class $P_I$from the others can have a positive response. Another method is called one-against-one (OAO) method. In OAO, for a P-class problem, $\frac{P(P-1)}{2}$ SVMs are constructed. Each of them is trained to separate one class from another class. While testing the system, one sample is input and it is tested for all the possible outputs of the classifier.

The idea of SVM is to implement the principle of structural risk minimization, which enables SVM to have excellent generalization ability in the situation when sample is very small. However the biggest problems while developing a SVM model are the selection of the kernel function and its parameter values. The penalty parameter *(C)* and the kernel function parameters such as the value of gamma *(γ)* for the radial basis function (RBF) kernel are optimized in SVM. Another problem in SVM classifier problem is to select the number of features. With a small and appropriate number of feature subsets, the classification design can be realized more easily. The main purpose of feature selection is to figure out the subset of features that represents the best recognition performance. Also, this results in less computational effort.

3.2.1. Features

Features of CCP (control chart patterns) are important because they represent the format of the control chart patterns. Accordingly, different control chart patterns have different properties that can be distinguished from their features. Therefore, it is very important to select the most suitable features for the signal recognition area not only to distinguish more or higher control chart patterns but also to lessen the computational effort and complexity of the classifier. Some of the suitable features are discussed below:

Shape Features:

- Slope of the least square line (*S*): *S* represents different formats for different CCPs. The magnitude of *S* for normal and cyclic patterns are almost zero. Whereas, for trend and shift pattern, they are more than zero.
- The number of mean crossings (*NC*): *NC* is another good feature to select for classifier problems. *NC* is highest for normal patterns. It is small for shift and trend patterns. For cyclic patterns, the number of crossings is intermediate between those for normal patterns and shift or trend patterns. Therefore, *NC* can easily differentiate normal patterns from cyclic patterns. It also differentiates normal and cyclic patterns from trend and shift patterns.
- The slope difference between the least-square line and the line segments representing a pattern (*SD*): The *SD* value can be obtained by subtracting the average slope as of the two line segments from the slopes of the least-square line. Normal, cyclic and trend patterns will have different *SD* values and thus, they can be distinguished from each-others using this feature.

Statistical Features:

Different statistical features like mean, standard deviation, skewness, kurtosis which are calculated by Eq. (8), Eq. (9), Eq. (10) and Eq. (11) respectively can be used in classifier problems, since statistical features are appropriate and distinguishable properties for different CCPs.

$$mean = \frac{\sum_{t=1}^{n} x_t}{n} \tag{8}$$

$$std = \sqrt{\frac{\sum_{t=1}^{n}(x_t - mean)^2}{n}} \tag{9}$$

$$skew = \frac{\sum_{t=1}^{n}(x_t - mean)^3}{n(std)^3} \tag{10}$$

$$kurt = \frac{\sum_{t=1}^{n}(x_t - mean)^4}{n(std)^4} \tag{11}$$

Here x_t represent the input (reference) vector and *n* is the total length of the observing window.

3.2.2 Framework:

In this paper, multiclass SVM has been used for classifying seven types of patterns. At first, model is trained. All the datasets are trained with their shape features, i.e., number of mean crossing (NC), mean, standard deviation, skewness. Matlab function 'multisvm' is used for training process. When testing data are given as input in the model, values of their shape features are calculated, and with reference of these values, our trained model identifies the pattern of input data. So, for recognizing control chart patterns using SVM, following steps were performed sequentially:

- Training all reference datasets with different features and assigning class labels to them
- Calculating the feature values of the randomly generated input datasets
- Different patterns of control charts are classified by incorporating the features' values to the trained SVM model.

4. Numerical Illustrations and Comparison

4.1 Statistical Correlation Coefficient method

Here six types of reference data are for six types of abnormal control chart patterns. A dataset is randomly generated and taken as input to check its relationship with reference patterns. Three important considerations are as follows.

- Reference data, are randomly generated.
- A threshold, h is assumed to be 0.4.
- Number of data for each type, n is 10.

Table 1. Reference datasets and input dataset

Reference dataset for upward shift pattern	Reference dataset for downward shift pattern	Reference dataset for upward trend pattern	Reference dataset for downward trend pattern	Reference dataset for cyclic pattern	Reference dataset for systematic pattern	Input dataset for testing
1.5164	-1.5120	0.1241	-0.1671	1.7698	-2.4973	2.1236
1.4947	-1.4879	0.2615	-0.2597	2.4832	2.5526	2.1672
1.4835	-1.5008	0.3647	-0.3608	1.7956	-2.4954	1.5439
1.5203	-1.5005	0.4842	-0.4696	0.0229	2.5268	3.4253
1.4668	-1.5519	0.6222	-0.5476	-1.8132	-2.5680	2.5564
1.5460	-1.5000	0.7081	-0.7453	-2.5152	2.4755	0.9552
1.5134	-1.4728	0.8001	-0.8468	-1.7748	-2.5604	0.8383
1.5218	-1.5232	0.9606	-0.9020	-0.0535	2.5280	0.7804
1.4766	-1.4550	1.0360	-1.0941	1.7922	-2.5348	1.7220
1.4590	-1.5042	1.1946	-1.2152	2.4534	2.5009	1.7936

Table 1 shows the randomly generated reference datasets for six types of patterns and an input dataset with a mean of 0 and standard deviation of 1. Now, an input dataset is tested against reference datasets of all types of patterns with the help of statistical correlation formula given in Eq. (1) and correlation coefficient between reference datasets and a test dataset $r_{u.s.}$, $r_{d.s.}$, $r_{u.t.}$, $r_{d.t.}$, r_{cyc} , r_{sys} are calculated respectively for upward shift, downward shift, upward trend, downward trend, cyclic and systematic patterns respectively. These coefficients are given below in Table 2.

Table 2. Values of Correlation Coefficient

Correlation coefficient	Values
$r_{u.s.}$	0.2698
$r_{d.s.}$	0.2294
$r_{u.t.}$	0.4101
$r_{d.t.}$	0.4365
r_{cyc}	0.2426
r_{sys}	0.0456

It is seen in Table 2 for our input dataset that correlation coefficient, $r_{d.t.}$ has the maximum value and it is greater than the threshold value of 0.4. Therefore, the pattern of our input test dataset is downward trend pattern.
One hundred datasets have been tested in this process and all these were randomly generated using the formulas of different types of control charts. Only 30 datasets yielded correct results and other datasets yielded incorrect results. As shown in Figure 8, this model's accuracy is 30% and error is 70%. Therefore, the probability of this model to produce correct result is 0.3.

4.2 Support Vector Machine method

After training the model with the help of shape and statistical features, different datasets are given as input. Table 3 illustrates six different randomly generated datasets for testing. Then their shape features are calculated and after that our trained model which already has been developed will identify the patterns. In the Table 4, shape features' values of six input datasets where each dataset contains 20 sample points and corresponding class labels of patterns identified by the trained model are given. These class labels are obtained from using our trained datasets which has been randomly generated using the reference Eq. (2-6) and their shape and statistical features are already stored in the programming model.

Table 3. Six input datasets

First dataset	Second dataset	Third dataset	Fourth dataset	Fifth dataset	Sixth dataset
1.3363	-0.3019	-2.1755	3.2163	-0.2286	0.5562
-0.3248	0.0507	1.9326	4.5629	-1.1092	1.4630
-1.2953	-3.0899	-2.2691	1.6111	-1.8589	-1.4551
-1.6724	0.3822	3.3364	-0.8585	0.0623	1.1888
-2.8702	-0.7132	-2.0776	-3.2645	-3.2674	1.1279
-0.5823	0.1045	2.7877	-2.1025	-0.7133	1.7329
0.7848	0.8268	-3.8505	-1.6964	-4.5487	-0.4102
1.0822	0.8882	2.0899	-0.1003	-1.5871	1.4001
-0.4757	-0.7096	-1.3117	1.3649	-1.8124	1.6230
0.3262	-0.4323	2.8097	2.4753	-1.9710	1.1841
-0.5168	0.3594	-1.0723	1.0130	-0.2122	3.4406
-2.0271	-1.1318	0.6415	0.7634	-3.2236	-0.3479
-1.4245	0.0567	-1.3198	-2.5635	-2.2446	1.2030
-1.0537	-0.9522	2.1152	-3.3754	-1.0340	2.4353
0.1212	-0.6042	-0.8117	-1.9764	-2.0461	1.9294
-0.0960	0.3617	1.8284	0.7640	-2.9671	3.0994
0.1564	0.3317	-1.9760	0.0977	-2.5010	2.0071
0.2012	-0.8275	2.1752	1.1679	-1.3298	2.0266
0.7754	0.7806	-1.9749	2.0053	-1.6595	3.7154
-0.3390	0.0625	2.2715	-0.6520	0.5307	0.5564

Table 4. Shape feature values of datasets and corresponding class labels of patterns

Shape Features		Class labels of patterns
Mean	Number of mean crossing	
-0.3947	9	1
-0.2279	13	1
0.1574	19	7
0.1122	19	6
-1.6863	3	2
1.4237	6	3

In our model, class labels 1,2,3,4,5,6,7 indicate normal, downward shift, upward trend, upward shift, downward trend, cyclic and systematic patterns respectively. In the SVM model, all the six test datasets are compared against all the trained datasets and they are classified according to the best matched trained datasets. This means our first input dataset is tested and our model identifies this as normal pattern. In this way our model calculates shape features of input datasets and identifies the class labels of patterns.

Another randomly generated one hundred datasets have been tested in this process. 85 datasets yielded correct results and other datasets yielded incorrect results. This can be concluded that 85% datasets can be recognized correctly with SVM model.

4.3 Comparison between traditional statistical correlation method and SVM method

From the above calculations of different datasets, it has been seen that the accuracy of statistical correlation coefficient method is only 30% which is very low to be used in a practical application. Compared to that SVM model has a much higher accuracy of 85%. However, SVM has some limitations. Its biggest limitation lies with the choice of kernel functions. It can also be abysmally slow in test phase. The most serious problem SVMs is high algorithmic complexity and extensive memory requirements. Although it has some limitations, it produces a more accurate result. Therefore, SVM model is always preferred given priority to the accuracy of the performance.

5. Conclusion and Future Works

With the increasing demand for varied products and emergence of many manufacturers for the same product, it has become the most important endeavor for the manufacturers to maintain a consistent quality of the products. As a result, any abnormal pattern in the manufacturing process needs to be recognized to take necessary steps to control the process. In this paper, we used two different approaches to recognize control chart patterns. The first approach, statistical correlation coefficient approach, is the simplest and traditional approach that needs the least computational effort. However, in this paper we can see that it produces accurate results for 30% of the time which is very low. Control chart pattern recognition using SVM model is a more advanced and accurate model than the statistical correlation model. It produces correct output for 85% of the time. However, SVM is the most expensive model where computational effort and complexity are also greater. For an industrial application SVM model will always be preferred to statistical correlation model for correct recognition of unnatural control chart patterns.

Future scope of this work includes using another method whose accuracy is higher and also don't possesses the disadvantages of SVM method so that it can perform control chart patterns' recognition more efficiently. Another future work is to overcome the limitations of SVM method. If this can be done, SVM will replace any other methods in control chart pattern recognition.

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