A Review on Input Features for Control Chart Patterns Recognition

Waseem Alwan, Adnan Hassan and Nor Hasrul Akhmal Ngadiman
Department of Materials, Manufacturing and Industrial Engineering, School of Mechanical Engineering, Faculty of Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor Bahru, Malaysia
wassemalwan@gmail.com, adnan@utm.my, norhasrul@utm.my

Abstract

Control chart pattern recognition (CCPR) is an essential tool for monitoring and diagnosing manufacturing process variability. It is used for recognizing manufacturing processes' abnormality. The specific type of patterns can be predicted with improved classification accuracy and less computational time when using appropriate features set in classifiers. Various features set extracted from process data streams have been proposed by researchers as input data representations for control chart pattern recognition (CCPR). This could confuse new researchers as to which features set need to be selected. Therefore, this paper aims to compare statistical features, shape features and mixed features as used in CCPR and identifies related open issues and research trends. This review concludes that mix features for input data representation are more promising to achieve a better recognition performance in terms of accuracy compared to the statistical and shape features.

Keywords
Control chart pattern recognition, Statistical features, shape features, mixed features.

1. Introduction
Abnormal patterns in control charts are associated with specific assignable causes that can adversely affect the process' stability. These abnormal patterns may to be recognized using machine learning technology where data representation is an essential part in the development of an automated control chart patterns recognizer. Features provide meaningful inputs containing information needed to classify control charts patterns. According to Addeh et al. (2018), using features set as input data representation can improve the performance of control chart pattern model. Feature-based control chart pattern recognizer (CCPR) has more flexibility especially when applied to complex process problems (Addeh et al. 2013). Features are useful in reducing the size of original raw data set and improving the predictive power (Pham and Wani 1997, Hassan et al. 2003, Ranaee and Ebrahimzadeh 2013, Zaman and Hassan 2019). If the features set are effectively mapped to the respective pattern classes, the possibility of having accurate prediction on process condition is higher. Furthermore, replacing raw data with feature characteristics allows a better interpretation of the prediction model, improves learning process' performances and efficacy by suppressing irrelevant and redundant data and reducing dimensionality (Masood and Hassan 2010).

Previous researchers such as Ghojogh et al. (2019), Hachicha and Ghorbel (2012), and Masood and Hassan (2012) published review papers related to this field. Ghojogh et al. (2019) gives a review on different feature extraction and selection methods and presented examples of their applications. Meanwhile, Hachicha and Ghorbel (2012) presented a survey paper on CCPR covering literatures between 1991 to 2010 and proposed their own conceptual classification scheme. They noted that most authors such as (Cheng and Hubele 1992, Hwarng and Chong 1995) had used raw data as their input data representation. From 2001 onwards, there has been an increase in the use of features as input data representation (Jin and Shi 2001, Guh and Shiue 2005, Yu et al. 2009). Masood and Hassan (2010) reviewed issues in development of ANN-based CCPR schemes with respect to input data representation, recognizer design and training, and multivariate process monitoring and diagnosis. Hassan et al. (2003) carried out a comparative study and confirmed that the use of the statistical features set had resulted in a significantly better recognition performance compared to raw data set.

There are many types of statistical features and geometrical features that have been used by researchers in CCPR. Choosing the right features set can be time-consuming and challenging for new researchers. For this reason, it is necessary to conduct a focused literature review on features as input data representation in CCPR. This review

investigates three features categories, namely statistical features, shape features and mixed features. Furthermore, this paper attempts to highlight related research issues and trends. The paper is organized as follows: Section 2 describes the methodology, Section 3 presents types of features, Section 4 analyses the trends in the application of features as input representation and finally Section 5 concludes the paper.

2. Methodology

This review paper focuses on popular input features being used by researchers in CCPR for quality monitoring and diagnosis. We searched literatures from Scopus, Web of Science, ScienceDirect Journal, and IEEE databases using the following keywords: statistical features, shape features, mixed features, control chart pattern recognition. It was found that there were 86 papers on CCPR published between 2010 to 2020. Out of these, a total of 36 papers focusing on statistical features, shape features, and mixed features (statistical and shape features) were selected for deeper analysis. Specifically, 11 papers used statistical features, six papers implemented shape features, and 19 papers used mixed features. All 36 selected papers used machine learning techniques as their pattern recognisers. Table 1 summarizes the selected journals.

Table 1. Distribution of reviewed articles based on the journal title.

Journal Name	Total Paper
ISA Transactions	4
IEEE	4
Pattern Analysis and Applications	3
Computers & Industrial Engineering	2
Journal of Physics: Conference Series	2
Computational Research Progress in Applied Science & Engineering	2
Materials Science and Engineering	2
Procedia Computer Science	2
European Journal of Industrial Engineering	1
Annals of Electrical and Electronic Engineering	1
Neural Computing and Applications	1
Journal of Intelligent Manufacturing	1
Procedia Engineering	1
International Journal of Engineering	1
Journal of Telecommunication, Electronic and Computer Engineering	1
Journal of Coastal Research	1
International Journal of Scientific & Engineering Research,	1
International Journal of Production Research	1
Mathematical Problems in Engineering	1
Applied Soft Computing	1
Journal of Engineering and Technology	1
International Journal of Advanced Manufacturing Technology	1
International Journal of Computer Aided Engineering and Technology	1
Total	36

To provide focus in this review, we excluded 50 papers, specifically, 11 papers used deep learning neural network, 11 papers used other features such as multi-resolution wavelets (MRW) and Euclidean distance, and 26 papers that utilized raw data as input representation. The papers that implemented deep learning neural network are excluded since the extracted features are relatively opaque to the users.

3. Types of Features

Machine learning techniques have been used to construct CCPR models to distinguish and classify types of patterns. These models' accuracy is dependent on the selected features and quality of information extracted from the features. In general, not all features used in specific pattern recognition are effective in distinguishing the patterns. Some features may be redundant or irrelevant, which may affect the classifier's accuracy. Therefore, features selection is an essential part in the application of machine learning techniques. In this review we divided futures into three categories, namely: statistical features, shape features, mixed between statistical and shape features. As shown in Figure 1, most of the previous CCPR studies implemented the combined shape and statistical features (50%). The statistical features (34%) and shape features (16%) categories are relatively less popular.

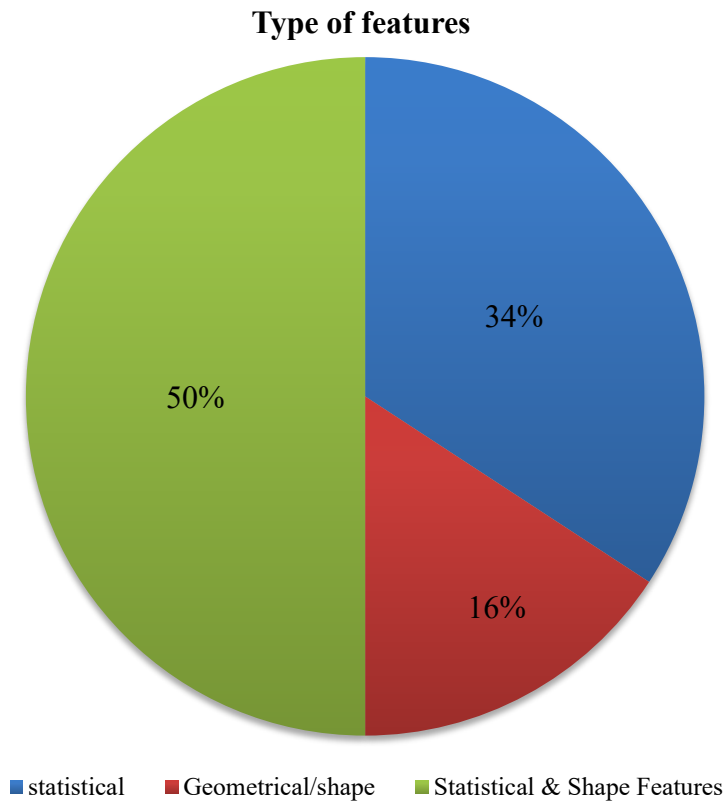

Figure 1: Category of features used in CCPR

3.1 Statistical Features

Statistical features provide quantitative information extracted from raw manufacturing data. Features extracted from raw data represent an approximation of the original raw data series in compact format. Statistical features measure different properties in the control chart patterns. Table 2 briefly introduces various types of statistical features, namely, Mean, Standard deviation, Skewness, Kurtosis, Slope, Mean-square value, Maximum cumulative summation (CUSUM), Average autocorrelations, Pearson correlation, Range, Smooth, Maximum differences between adjacent values, Maximum gradient, Maximum-likelihood estimation and central moment order (Hassan et al. 2003, Lavangnananda and Khamchai 2015, Lavangnananda and Waiwing 2015, Bayati 2017, Rahman et al. 2017, Haghighati and Hassan 2018, Sohaimi et al. 2018, Haghighati and Hassan 2019, Zaman and Hassan 2019).

From Table 3, it can be observed that the most popular statistical features used by researchers are Mean and Standard deviation. The second most common features are Skewness and Kurtosis which were implemented by five researchers. The third most common feature is Slope as it was implemented by four researchers. The fourth most common feature is the Cumulative Sum, where three researchers have implemented it. The fifth most common features are Mean-square value. Average Autocorrelations and Pearson Correlation were implemented by two researchers. The least popular features are Range, Smooth, Maximum Differences Between Adjacent Values, Maximum Gradient, Maximum-likelihood Estimation, and Central Moment of Order were used by only one researcher. Based on Table 3, Mean (MEAN), Standard Deviation (STD), Skewness (SKEW), Kurtosis (KUR) and Slope (SLOPE) are the most commonly used features from the statistical features category. These features describe the data distribution variables clearly and reported to have improved results in recognizing pattern types in control charts. The use of statistical features has enabled researchers like Zaman and Hassan (2019) to achieve 99.82% recognition accuracy. Haghighati and Hassan (2018) reported an improved recognition accuracy of imputed dataset (99.2%) when using the statistical features.

Table 2: Description of statistical features (Haghighati and Hassan 2019, Zaman and Hassan 2019)

Statistical features	Description
Mean	The average of observation values
Standard deviation (StD)	Measures how much the observed values differ from the mean value for the observation
Skewness (SKEW)	Provides information concerning the shape of the distribution. It indicates any lack of symmetry in the data distribution
Kurtosis (KUR)	Measures the peakness of a distribution
Slope (SLOPE)	Measures the relationship between two variables to estimate the average rate of change
Mean-square value (MSV)	The average power of the sample value, $MSV = \frac{1}{n+1}\sum_{i=1}^{n} {X_i}^2$ where X_i are the individual values and n is the number of points or window size
Maximum CUSUM (CUS)	Cumulative sum (CUSUM) monitor shifts in the process mean and provides the cumulative sum of deviations from a target.
Average autocorrelation of lag 1 and 2 (ACOR)	Average autocorrelation (ACOR) measures the dependence of a data between any two neighbouring values. The averages for autocorrelation at lag 1 and 2 can be used as the feature
Pearson correlation	Measures the correlation between the strength and direction of two variables based on the linear relationship.
Range (RANGE)	Represents the difference between the maximum and minimum values
Smooth	An approximation function to capture basic patterns and to leave out the noisy data.
Maximum differences between adjacent values	Provides the maximum differences between adjacent observations
Maximum gradient	The maximum slope
Maximum-likelihood estimation (MLE)	Estimates the parameters of a probability distribution that involves maximizing a likelihood function to find the probability distribution and parameters that best explain the observed data.
The central moment of order	Provides deviations from the mean since the higher-order central moments relate only to the spread and shape of the distribution.

Table 3: Summary of statistical features by the name of authors who have implemented them.

Author name (year)	Mean	StD	SKEW	KUR	Slop	MSV	CUS	ACOR	PC	RANGE	Smooth	MDBAV	MG	MLE	CMOO
Haghighati and Hassan (2019)	x	x	x	x											
Zaman and Hassan (2019)	x	x	x	x	x	x	x	x							
Haghighati and Hassan (2018)	x	x	x	x			x			x	x	x	x	x	x
Sohaimi et al. (2018)	x	x													
Bayati (2017)	x	x													
Rahman et al. (2017)	x	x													
Masood and Shyen (2016)	x	x													
Rahman et al. (2016)	x	x													
Lavangnananda and Khamchai (2015)	x	x	x	x	x				x						
Lavangnananda and Waiwing (2015)	x	x	x	x	x				x						
Hassan (2011)	x	x			x	x	x	x							

3.2 Shape Features

Graphical display of control chart patterns provides useful information on process variations. Different shapes of time series data can be observed representing various conditions of the process. The shape features as found in the CCPR literatures are summarized in Table 4. These shape features are compiled from (Bag et al. 2012, Addeh and Maghsoudi 2016, Wong and Chua 2019, Lu et al. 2020).

Table 4: description of shape features (Addeh and Maghsoudi 2016, Wong and Chua 2019).

Shape features	Description
LSLS	The least-square line slope of the pattern. This feature distinguishes the normal and cyclic patterns from the shift and trend patterns.
NC1	The crossings mean line value of the pattern. This feature differentiates natural patterns from cyclic patterns. It also distinguishes natural and cyclic patterns from shift and trend patterns.
NC2	Least-square line crossings value. This feature is used to distinguish trend and normal patterns from other patterns.
AS	The slope line segments average. This feature separates the trend patterns from other patterns.
SD	The slope difference between the least-square line and the line segments representing a pattern. This feature separates the shift pattern from other patterns.
APML	The area between the pattern and the mean line. This feature distinguishes between natural patterns and other patterns.
APSL	The area between the pattern and its least-square line. This feature distinguishes cyclic and shift patterns from trend and normal patterns.
ASS	The area between the least-square line and the line segments. This feature is approximately equal zero for trend pattern and is higher for the shift pattern. It distinguishes shift pattern from trend patterns.
REAE	The ratio of variance of the observations (SD^2) and average MSE of the LS lines fitted to six subsets of N/2 data points.
SB	Sign of slope of the LS line representing the overall pattern.
ADIST	Average distance between the consecutive points in terms of SD.
SRANGE	Range of slopes of straight lines passing through six pair wise combinations of midpoints of four equal segments.
RVE	Ratio between variance of the data points in the observation window (SD2) and mean sum of squares of errors (MSE) of the LS line representing the overall pattern.
ALSPI	Area between the overall pattern and LS line per interval in terms of SD2.
SABL	Sign of average slope of the LS lines fitted to six subsets of N/2 data points.
DBRANGE	Range of slopes of the LS lines fitted to four subsets of observations.
REPEPE	Ratio of MSE of the LS line representing the overall pattern and PMSE of the LS lines fitted to two segments.
RVPEPE	Ratio of variance of observations SD2 and PMSE of the LS lines fitted to two segments.
PSMLSC	Proportion of the sum of number of crossovers to mean line and LS line.
SASDPE	Sum of absolute slope difference between the LS line representing the overall pattern and the individual line segment.

Previous studies that have implemented the respective shape features are listed in Table 5.

Table 5: Summary of previous works that have implemented shape features

Author name (year)	SD	LSLS	NC1	ALSPI	AS	REAE	APML	ASS	RVE	SRANGE	SB	DBRANGE	RVPEPE	REPEPE	SABL	APSL	NC2	PSMLSC	SASDPE	ADIST
Lu et al. (2020)	x								x	x	x									x
Wong and Chua (2019)			x		x		x	x												
Addeh and Maghsoudi (2016)	x	x	x		x		x	x								x	x			
Addeh (2016)	x			x		x						x	x	x	x					
Chompu-Inwai and Thaiupathump (2015)		x																		
Bag et al. (2012)				x		x			x	x	x							x	x	

Table 5 shows the most popular shape features is are the slope difference between the least-square line and line segments represents a pattern (SD) it has been implemented by three out of six researchers. The second most common

features are The least-square line slope of the pattern (LSLS), The crossings mean line value of the pattern (NC1), Area between the overall pattern and LS line per interval in terms of SD2 (ALSPI), The slope line segments average (AS), Ratio of mean sum of squares of errors (MSE) of the LS line fitted to overall data and average MSE of the LS lines fitted to six subsets of N/2 data points (REAE), The area between the pattern and the mean line (APML), areas between the least-square line and line segments (ASS), Ratio between variance of the data points in the observation window (SD2) and mean sum of squares of errors (MSE) of the LS line representing the overall pattern (RVE), Range of slopes of straight lines passing through six pair wise combinations of midpoints of four equal segments (SRANGE) and Sign of slope of the LS line representing the overall pattern (SB). The least popular shape features are Range of slopes of the LS lines fitted to four subsets of observations (DBRANGE), Ratio of variance of observations SD2 and PMSE of the LS lines fitted to two segments (RVPEPE), Ratio of MSE of the LS line representing the overall pattern and PMSE of the LS lines fitted to two segments (REPEPE), Sign of average slope of the LS lines fitted to six subsets of N/2 data points (SABL), The area between the pattern and its least-square line (APSL), Least-square line crossings value (NC2), Proportion of the sum of number of crossovers to mean line and LS line (PSMLSC), Sum of absolute slope difference between the LS line representing the overall pattern and the individual line segment (SASDPE) and Average distance between the consecutive points in terms of SD (ADIST) were only used by one researcher.

3.3 Mixed Statistical and Shape Features

Some researchers have used mixed features statistical and shape as input data representation for CCPR. Table 6 provides a summary of these mixed features.

Table 6: Summary of mixed statistical and shape features by the name of authors who have implemented them.

Author name (year)	Mean	Std	SKEW	KUR	MSV	CUSM	(ACOR)	cvm & cvs	LSLS Slop	NC1	NC2	AS	SD	APML	APSL	ASS	AASL	SRANGE	ACLPI	SB	PSMLSC	REAE	ABDPE	AMEMBER	MVSASTI
Aziz kalteh and Babouei (2020)		x							x	x	x		x	x	x										x
Zhang et al. (2020)	x	x	x	x	x	x	x		x	x	x			x	x										
Zhang et al. (2020)	x	x	x	x	x	x	x		x	x	x			x	x										
Zhou et al. (2018)								x	x	x	x														
Addeh et al. (2018)	x	x							x			x	x			x									
Addeh et al. (2018)	x								x				x	x	x										
Zhao et al. (2017)	x	x	x	x	x		x										x	x	x	x	x	x			
Pelegrina et al. (2016)	x									x			x										x		x
Zhang et al. (2015)	x	x	x	x	x	x	x		x	x	x			x	x										
Khajehzadeh and Asady (2015)	x	x	x	x			x		x	x	x	x	x	x	x	x									
Wu et al. (2015)	x	x	x	x			x									x	x	x	x	x	x	x	x		
Zhang and Cheng (2015)	x	x	x	x	x	x	x		x	x	x			x	x										
Addeh et al. (2014)	x													x	x	x									x
Ebrahimzadeh et al. (2013)	x													x	x	x									x
Addeh et al. (2013)	x	x												x		x					x		x	x	
Ranaee and Ebrahimzadeh (2013)	x	x	x	x					x	x	x	x	x	x	x	x									
Cheng et al. (2012)	x	x					x																		
Addeh et al. (2011)	x													x											x
Ranaee et al. (2010)	x													x		x									

Table 6 shows that the most popular feature is Mean since it has been implemented by 17 out of 19 researchers. The second popular feature is the area between the pattern and the mean line (APML) as it was used by 13 researchers

followed by standard deviation (SD) the third popular feature, which was utilized by 12 researchers. The fourth popular features, which was implemented by 10 researchers, are the least-square line slope of the pattern (LSLS) and the area between pattern and its least-square line (APSL). The fifth popular features were also used by 9 researchers namely crossings mean line value of the pattern (NC1). The sixth popular features are Skewness (SKEW), Kurtosis (KUR), average autocorrelations, the area between the least-square line and line segments (ASS) and Least-square line crossings value (NC2) that was used by 8 researchers. The seventh popular features utilized by 6 researchers is slope difference between the least-square line and line segments representing a pattern (SD). The eighth popular feature is the maximum variation in signal amplitude in a short time interval (MVSASTI) where five researchers adopted them in their work. The ninth popular feature used by 4 researchers is namely Cumulative sum, followed by the ninth popular features adapted by 3 researchers, the slope line segments average (AS) and the ratio of average for intersection number of mean line and least square line (PSMLSC) and Absolute slope difference between the LS line representing the overall pattern and the line segments representing patterns within the two segments (ABDPE). The eleventh popular features used by 2 researchers are the mean for midpoint slope (AASL), the range of midpoint slope (SRANGE), ratio of the area of variance for model and mean line (ACLPI), symbol for the entire model least-squares line (SB), the ratio of the average of mean-variance (REAE). As the least popular features, Coefficient of mean variation at a later stage (cvm), Coefficient of standard deviation variation at a later stage (cvs) and Cyclic membership (AMEMBER) were only used by one researcher.

Addeh et.al (2018) proposed to use association rules method for selecting suitable statistical and shape features. The association rules have been used in neural networks to capture nonlinear relationships between input-output. The most used artificial neural networks (ANN) for CCPR classification is the feed-forward network, including multilayer perceptron and radial basis function (RBF) networks. Another popular ANN is the Self-Organizing Map (SOM), or Kohonen-Network, mainly used for data clustering and feature mapping.

4. Trend in the application of features as input representation

The cumulative distribution of published works for the three categories of features based on the year of study is shown in Figure 2.

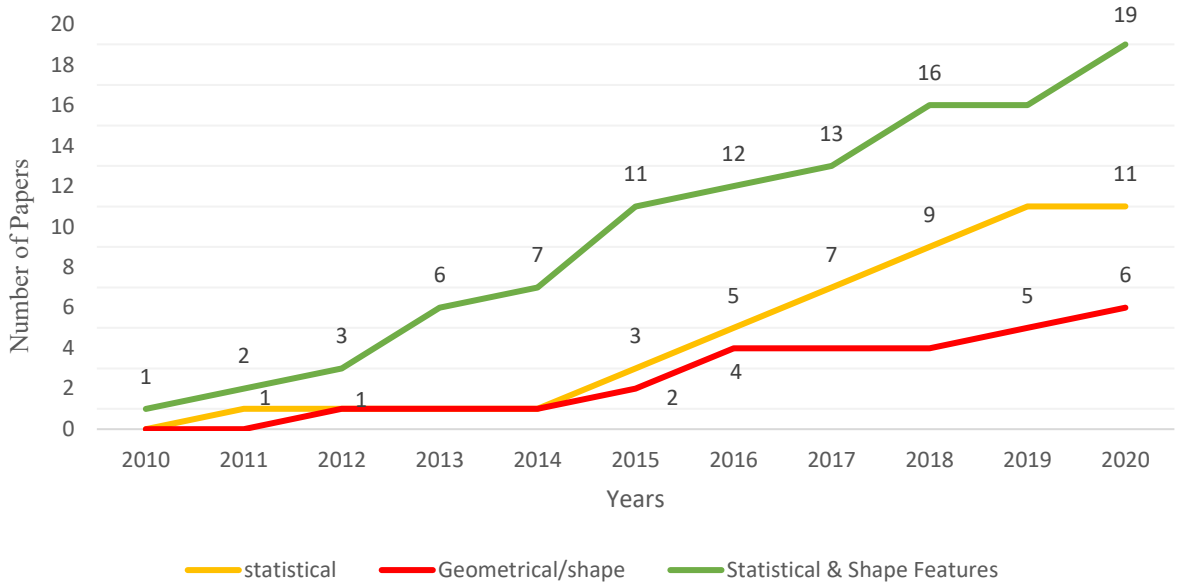

Figure 2: Cumulative of Publication Based on Feature Categories.

Figure 2 shows that the mixed statistical and shape features category is the most popular. It is an increasing trend from one publication in 2010 to 19 cumulative publications in 2020. In 2020, two papers published used mixed statistical and shape features while one paper used shape features. Overall, up to February 2020, a total of 19 papers published used mixed statistical and shape features, whilst 11 papers used statistical features, and only six papers used shape features.

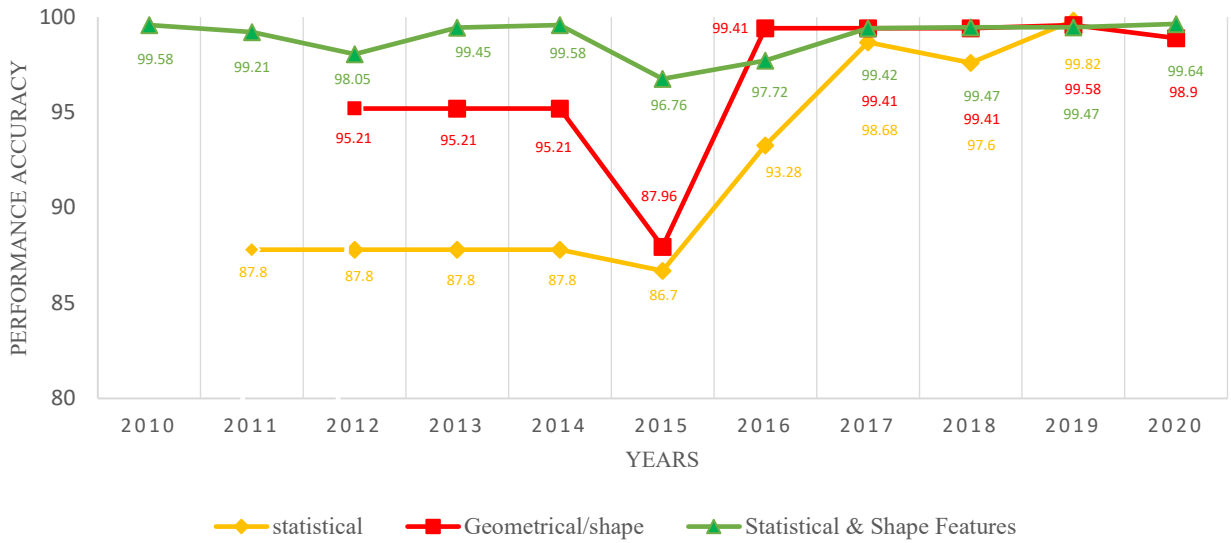

Figure 3: features response based on accuracy.

Figure 3 provides indicative performance in term of recognition accuracy for the existing features based CCPR schemes. Between 2011 to 2015, results from Figure 3 suggest that statistical features and shape features on their own are relatively less accurate compared to when they were concurrently implemented (mixed features). Ranaee et al. (2010) and Addeh et al. (2013) argued that the mixed features have excellent discrimination ability for pattern classification. This review confirms their arguments, particularly between 2010 to 2015. However, generally from 2017 onwards various researchers have reported improved performance for unmixed shape features and unmixed statistical features (>99% accuracy).

5. Conclusion

Accurate recognition of control chart patterns (CCPs) is critical in process monitoring and diagnosis especially when producing high-quality products. This paper provides a literature review on input data representation for three categories of features and their recognition accuracies. This review observes the following findings:

1. The most used features during the publication period from 2010 to 2020 are the mixed features. A total of 19 papers reviewed used mixed (statistical and shape) features, 11 papers on statistical features, and six papers on shape features.
2. The Mean feature is one of the most popular statistical features where 15 researchers have adopted them in the mixed features category. The standard deviation (Std) has been used by ten researchers. Both mean and standard deviation features provide effective representation of process variability information to classify types of CCPR patterns.
3. For the shape features category, the area between the pattern and the mean line (APML) feature is the most popular feature as 12 papers used the feature as part of their methodology.
4. In shape features, data representation does not dependent on the sample size. This limitation opens opportunity for further study to see how it may affect its robustness in data representation.
5. The literature suggests that when statistical features and shape features are concurrently implemented, they can give better recognition accuracy as compared to unmixed other features especially during the early years. However, latest literatures indicate the gap is narrowing.

This review provides a starting point for new researchers to select suitable features for input data representation in developing CCPR schemes. Investigating the relationship between input data representation and recognizer design can be an interesting area for future research.

Acknowledgements

The authors thank to the Ministry of Higher Education Malaysia and Research Management Centre, Universiti Teknologi Malaysia through FRGS-UTM Grant No: Q.J130000.2551.21H58 for financial support to enable this publication.

References

Addeh, A., Control Chart Pattern Recognition Using Associated Rules and Optimized Classifier, *Computational Research Progress in Applied Science & Engineering,* vol. 2, pp. 71-80, 2016.

Addeh, A., Khormali, A., and Golilarz, N. A., Control chart pattern recognition using RBF neural network with new training algorithm and practical features, *ISA Transactions,* vol. 79, pp. 202-216, 2018.

Addeh, A., and Maghsoudi, B. M., Control chart patterns detection using COA based trained MLP neural network and shape features, *Computational Research Progress in Applied Science & Engineering,* vol. 2, pp. 5-8, 2016.

Addeh, A., Zarbakhsh, P., Seyedzadeh Kharazi, S. J., and Harastani, M., A Hierarchical System for Recognition of Control Chart Patterns, *International Conference on Advances in Computing and Communication Engineering (ICACCE-2018), IEEE,* Paris, France, pp. 423-427, June 22-23, 2018.

Addeh, J., Ebrahimzadeh, A., Azarbad, M., and Ranaee, V., Statistical process control using optimized neural networks: A case study, *ISA Transactions,* vol. 53, no. 5, pp. 1489-1499, 2014.

Addeh, J., Ebrahimzadeh, A., and Nazaryan, H., A Research about Pattern Recognition of Control Chart Using Optimized ANFIS and Selected Features, *Journal of Engineering & Technology,* vol. 3, pp. 1,2013.

Addeh, J., Ebrahimzadeh, A. and Ranaee, V., Control chart pattern recognition using adaptive back-propagation artificial Neural networks and efficient features, *Proceedings of the 2nd International Conference on Control, Instrumentation and Automation, IEEE*, pp. 742-746, 2011.

Aziz kalteh, A., and Babouei, S., Control chart patterns recognition using ANFIS with new training algorithm and intelligent utilization of shape and statistical features, *ISA Transactions,* vol. 102, pp. 12-22,2020.

Bag, M., Gauri, S. K., and Chakraborty, S., An expert system for control chart pattern recognition, *International Journal of Advanced Manufacturing Technology,* vol. 62, no. 1-4, pp. 291-301, 2012.

Bayati, N., Pattern recognition in control chart using neural network based on a new statistical feature, *International Journal of Engineering,* vol. 30, no. 9, pp. 1372-1380, 2017.

Cheng, C.-S., and Hubele, N. F., Design of a knowledge-based expert system for statistical process control, *Computers & industrial engineering,* vol. 22, no. 4, pp. 501-517, 1992.

Cheng, C. S., Huang, K. K., and Chen, P. W., Recognition of control chart patterns using a neural network-based pattern recognizer with features extracted from correlation analysis, *Pattern Analysis and Applications,* vol. 18, no. 1, pp. 75-86, 2012.

Chompu-Inwai, R., and Thaiupathump, T., Improved ICA-based mixture control chart patterns recognition using shape related features, *Proceedings of IEEE Conference on Control and Applications (CCA)*, pp. 484-489, Sep 21, 2015.

Ebrahimzadeh, A., Addeh, J., and Ranaee, V., Recognition of control chart patterns using an intelligent technique, *Applied Soft Computing,* vol. 13, no. 5, pp. 2970-2980, 2013.

Ghojogh, B., Samad, M. N., Mashhadi, S. A., Kapoor, T., Ali, W., Karray, F., and Crowley, M., Feature selection and feature extraction in pattern analysis: A literature review, *arXiv preprint arXiv*, 1905.02845, May 7, 2019.

Guh, R.-S., and Shiue, Y.-R., On-line identification of control chart patterns using self-organizing approaches, *International Journal of Production Research,* vol. 43, no. 6, pp. 1225-1254, 2005.

Hachicha, W., and Ghorbel, A., A survey of control-chart pattern-recognition literature (1991–2010) based on a new conceptual classification scheme, *Computers & Industrial Engineering,* vol. 63, no. 1, pp. 204-222, 2012.

Haghighati, R., and Hassan, A., Recognition performance of imputed control chart patterns using exponentially weighted moving average, *European Journal of Industrial Engineering,* vol. 12, no. 5, pp. 637-660, 2018.

Haghighati, R., and Hassan, A., Feature extraction in control chart patterns with missing data, *Journal of Physics: Conference Series, IOP Publishing,* vol. 1150, no. 1, pp. 012013, 2019.

Hassan, A., An improved scheme for online recognition of control chart patterns, *International Journal of Computer Aided Engineering and Technology,* vol. 3, no. 3-4, pp. 309-321, 2011.

Hassan, A., Baksh, M. S. N., Shaharoun, A. M., and Jamaluddin, H., Improved SPC chart pattern recognition using statistical features, *International Journal of Production Research,* vol. 41, no. 7, pp. 1587-1603, 2003.

Hwarng, H., and Chong, C., Detecting process non-randomness through a fast and cumulative learning ART-based pattern recognizer, *International Journal of Production Research,* vol. 33, no. 7, pp. 1817-1833, 1995.

Jin, J., and Shi, J., Automatic feature extraction of waveform signals for in-process diagnostic performance improvement, *Journal of Intelligent Manufacturing,* vol. 12, no. 3, pp. 257-268, 2001.

Khajehzadeh, A., and Asady, M., Recognition of control chart patterns using adaptive neuro-fuzzy inference system and efficient features, *Int J Sci Eng Res,* vol. 6, no. 9, pp. 771-779, 2015.

Lavangnananda, K., and Khamchai, S., Capability of Control Chart Patterns Classifiers on Various Noise Levels, *Procedia Computer Science,* vol. 69, pp. 26-35, 2015.

Lavangnananda, K., and Waiwing, S., Effectiveness of Different Preprocessing Techniques on Classification of Various Lengths of Control Charts Patterns, *Procedia Computer Science,* vol. 69, pp. 44-54, 2015.

Lu, Z., Wang, M., and Dai, W., A condition monitoring approach for machining process based on control chart pattern recognition with dynamically-sized observation windows, *Computers and Industrial Engineering 142*, Apr 1, 2020.

Masood, I., and Hassan, A., Issues in development of artificial neural network-based control chart pattern recognition schemes, *European Journal of Scientific Research,* vol. 39, no. 3, pp. 336-355, 2010.

Masood, I., and Shyen, V. B. E., Quality control in hard disc drive manufacturing using pattern recognition technique, *IOP Conference Series: Materials Science and Engineering,* vol. 160, no. 1, pp. 012008, Nov. 1, 2016.

Pelegrina, G. D., Duarte, L. T., and Jutten, C., Blind source separation and feature extraction in concurrent control charts pattern recognition: Novel analyses and a comparison of different methods, *Computers & Industrial Engineering,* vol. 92, pp. 105-114, 2016.

Pham, D. T., and Wani, M. A., Feature-based control chart pattern recognition, *International Journal of Production Research,* vol. 35, no. 7, pp. 1875-1890, 1997.

Rahman, N. A., Masood, I., and Rahman, M. N. A., Recognition of unnatural variation patterns in metal-stamping process using artificial neural network and statistical features, *IOP Conference Series: Materials Science and Engineering,* vol. 160, no. 1, pp. 012006, Nov.1, 2016.

Rahman, N. A., Masood, I., Rahman, M. N. A., and Nasir, N. F., Control chart pattern recognition in metal stamping process using statistical features-ANN, *Journal of Telecommunication, Electronic and Computer Engineering,* vol. 9, no. 3-2, pp. 5-9, 2017.

Ranaee, V., and Ebrahimzadeh, A., Control chart pattern recognition using neural networks and efficient features: a comparative study, *Pattern Analysis and Applications,* vol. 16, no. 3, pp. 321-332, 2013.

Ranaee, V., Ebrahimzadeh, A., and Ghaderi, R., Application of the PSO–SVM model for recognition of control chart patterns, *ISA transactions,* vol. 49, no. 4, pp. 577-586, 2010.

Sohaimi, N., Masood, I., and Md Nor, D., Bivariate SPC Chart Pattern Recognition Using Modular-Neural Network, *IOP Conference Series: Journal of Physics,* vol. 1049, no. 1, pp. 012096, Jul. 1, 2018.

Wong, P., and Chua, A., Control chart pattern identification using a synergy between neural networks and bees algorithm, *Annals of Electrical and Electronic Engineering,* vol. 2, pp. 8-13, 2019.

Wu, C., Liu, F., and Zhu, B., Control chart pattern recognition using an integrated model based on binary-tree support vector machine, *International Journal of Production Research,* vol. 53, no. 7, pp. 2026-2040, 2015.

Yu, J., Xi, L., and Zhou, X., Identifying source(s) of out-of-control signals in multivariate manufacturing processes using selective neural network ensemble, *Engineering Applications of Artificial Intelligence,* vol. 22, no. 1, pp. 141-152, 2009.

Zaman, M., and Hassan, A., Improved statistical features-based control chart patterns recognition using ANFIS with fuzzy clustering, *Neural Computing and Applications,* vol. 31, no. 10, pp. 5935-5949, 2019.

Zhang, M., and Cheng, W., Recognition of Mixture Control Chart Pattern Using Multiclass Support Vector Machine and Genetic Algorithm Based on Statistical and Shape Features, *Mathematical Problems in Engineering,* Nov 1, 2015.

Zhang, M., Cheng, W., and Guo, P., Intelligent recognition of mixture control chart pattern based on quadratic feature extraction and SVM with AMPSO, *Journal of Coastal Research*, vol. 73, pp. 304-309, Mar, 2015.

Zhang, M., Yuan, Y., Wang, R., and Cheng, W., Recognition of mixture control chart patterns based on fusion feature reduction and fireworks algorithm-optimized MSVM, *Pattern Analysis and Applications,* vol. 23, no. 1, pp. 15-26, 2020.

Zhang, M., Zhang, X., Wang, H., Xiong, G., and Cheng, W., Features Fusion Exaction and KELM with Modified Grey Wolf Optimizer for Mixture Control Chart Patterns Recognition, *IEEE Access,* vol. 8, pp. 42469-42480, 2020.

Zhao, C., Wang, C., Hua, L., Liu, X., Zhang, Y., and Hu, H., Recognition of Control Chart Pattern Using Improved Supervised Locally Linear Embedding and Support Vector Machine, *Procedia Engineering,* vol. 174, pp. 281-288, 2017.

Zhou, X., Jiang, P., and Wang, X., Recognition of control chart patterns using fuzzy SVM with a hybrid kernel function, *Journal of Intelligent Manufacturing,* vol. 29, no. 1, pp. 51-67, 2018.

Biographies

Waseem Alwan received his B.S. degree in mechanical engineering and higher Diploma degree in Computer Aided in Instructional engineering from University of Technology, Iraq, in 1999 and 2001, respectively. And his M.S. degree in mechanical and manufacturing engineering from Universiti Tun Hussein Onn Malaysia, Malaysia, in 2019. He is currently a doctoral student in industrial engineering, Universiti Teknologi Malaysia. His research interests include Control Chart patterns Recognition.

Adnan Hassan is an Associate Professor in the School of Mechanical Engineering, Universiti Teknologi Malaysia (UTM). He received a B.Sc. (Hons.) in Industrial Engineering from the University of Miami, Florida, U.S.A (1986), a M.Sc. in Industrial Measurement Systems from Brunel University, U.K. (1992), and a Ph.D in Mechanical Engineering from UTM (2003). From 2007 to 2009, he was the Head of Manufacturing and Industrial Engineering Department at UTM. From Nov 2009 till June 2011, he was seconded to King Abdul Aziz University (KAU), Saudi Arabia where he was the founding Chairman for the Department of Industrial Engineering, KAU Rabigh Branch. His research interest includes pattern recognition for process monitoring, supply chain, maintenance, and performance measure.

.

Nor Hasrul Akhmal Ngadiman received his Bachelor of Engineering in Mechanical Engineering (Industry) degree from Universiti Teknologi Malaysia (UTM) in 2012. Based on his excellent achievement in academic and extra-curricular activities, he was offered the opportunity to pursue his Doctor of Philosophy (PhD) degree directly after his first degree via UTM's Fast Track Programme. He embraced the challenge, and with diligence and perseverance he obtained his PhD in Mechanical Engineering from UTM in 2016. He is currently Senior Lecturer in the Department of Materials, Manufacturing and Industrial Engineering, School of Mechanical Engineering, Faculty of Engineering (FE), UTM, Johor Bahru, Johor, Malaysia. Dr. Hasrul is involved (both as Project Leader and Project Member) in numerous research projects funded by the Ministry of Education and various industries as well as by the UTM. His papers have been published in both international and national journals. In addition to this, he has presented papers at international and national conferences and seminars and obtained over 241 citations and H- index 7. Dr. Hasrul is engaged with several consultancy projects involving local companies and organizations and has conducted training on diverse courses organized by the university.