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Anomaly Detection in Yarn Tension Signal Using Independent Component Analysis

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Abstract: Finding patterns in data that defy expected behavior is what anomaly detection entails. In many application fields, these incorrect patterns are referred to as contaminants, abnormalities, exceptions, or outliers. The significance of anomaly detection is that it helps to identify irregularities in data across a range of application domains and turns them into valuable information. When the yarn tension signals are inspected, anomaly states in the signals are seen in situations where it defect for whatever reason. This distinction makes it possible to predict whether the twister is malfunctioning. So, a bigger issue is avoided. The employment of Cluster-Based Algorithms, Statistical Method Algorithms, and other techniques to identify anomalies is common in the literature. The yarn tension signals in the twisting machines have been analyzed in this work using independent component analysis, and the problematic signal locations have been identified. The proposed method has been contrasted with other ways, and it has produced the highest success rate.

Key words: Anomaly detection, defect diagnosis, ICA, twister, yarn tension signal.

Bağımsız Bileşen Analizi Kullanılarak İplik Gerginlik Sinyalinde Anormallik Tespiti

Öz: Anormallik tespiti, verilerde beklenen davranışı göstermeyen kalıpların elde edilmesine karşılık gelmektedir. Bu uygun olmayan kalıplar, farklı uygulama etki alanlarında anormallikler, istisnalar, aykırı değerler veya kirleticiler olarak adlandırılır. Anormallik tespitinin önemi, çeşitli uygulama alanlarındaki verilerdeki anormalliklerin önemli bilgilere dönüşmesidir. İplik gerginlik sinyalleri incelendiğinde herhangi bir nedenle arıza yaptığı durumlarda bu sinyallerde anormallik durumları gözlemlenmektedir. Bu farklılıktan yola çıkarak iplik bükme makinesinde, bir arıza olup olmadığı önceden tespit edilebilir. Böylece daha büyük bir sorunun önüne geçilmiş olmaktadır. Anormallikleri tespit etmek için literatürde birçok yöntem kullanılmaktadır: Küme Tabanlı Algoritmalar, İstatistiksel Yöntem Algoritmaları vb. Bu çalışmada, bağımsız bileşen analizi kullanılarak, iplik makinelerinde bulunan iplik gerilim sinyalleri incelenmiş ve hatalı sinyal bölgeleri incelenmiştir. belirlenen. Önerilen yöntem diğer yöntemlerle karşılaştırılmış ve önerilen yöntemle en yüksek başarı oranı elde edilmiştir.

Anahtar kelimeler: Anormallik tespiti, arıza teşhisi, BBA, iplik bükme makinesi, iplik gerilim sinyali.

1. Introduction

To identify unexpected flaws in the yarn quality control system, the tension signal model in the yarn twisting machine should be examined. However, due to some unidentified noise that alters the wave appearance of the twisted yarn tension signal in various manufacturing locations or production processes, this analysis method is quite challenging [1]. On the spinning machine, a few methods can be used to extract the tension signal from the noise signal. Unknown noises confuse the yarn tension signal. The wave appearance of the tension signals in the yarn twisting machine is generally affected by noise during the yarn twisting operation. Uncertain signals (such as electrical noise, mass change, vibration disturbance, etc.) cause noise irregularity [2]. The tension sensor must be able to distinguish between even the tiniest variations in thread tension and eliminate noise—higher frequency variations—from the signal [3].

The quality control system fails to appropriately identify atypical flaws as a result of noise incidents. For signal processing to correctly categorize all kinds of odd voltages, a strong filter is required. Traditional low-pass filters, however, sometimes fail to successfully suppress noise. In order to reduce noise, the conventional low-pass filter often uses frequency-assigned information. Designing the filter function and multiplying the measurement signal by the filter function is the fundamental technique for the conventional low pass filter. High-frequency

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noise-related components in the signal are reduced using the filter function. However, the typical filter struggles to produce noise in the presence of a low-frequency noise signal. For instance, the mass change of material in the twister machine is seen as noise. This noise is broadcast in the low-frequency region, which is also the region where the primary voltage signal is broadcast. The conventional low-pass filter has a difficult time removing this noise (mass change). Figure 1 depicts how an exemplary yarn twist machine looks.

Figure 1. Example of a twister yarn machine [4].

In order to perform Sparse Kernel Principal Component Analysis (SKPCA) for outlier detection, Das et al. [5] proposed a novel method. On five real-world datasets, they examined them, and they found that by employing just 4% of the main components (PCs). A different study [6] advocated for detecting anomalies in hyperspectral data using a selective kernel principal component analysis approach. The kernel principal component analysis (KPCA) step in this approach is the first step in thoroughly mining the high-order correlation between spectral bands. Then, in regional events, high-order statistics are used to determine the local average singularity.

Mei et al. [7] suggested using an independent component analysis (ICA) technique to find anomalies in hyperspectral imaging. Kernel Principal Component Analysis (KPCA) is performed on a feature space in order to whiten the data and fully mine the nonlinear information between spectral bands. Then, ICA examines the projection directions in the KPCA-whitened space to carry out a mutually independent distribution of the calculated data. Applying ICA after random massive reductions was indicated in a different study as a way to reduce EEG signals with artifacts [8]. Zonglin et al. [9] presented a multidimensional traffic anomaly detection system based on ICA. They employed ICA to separate the potentially anomalous component from a particular traffic signal's time and frequency domain properties. Zunic et al. [10] published an original method for locating various forms of abnormalities in GPS data. The connection between detecting a QRS complex in a GPS signal and an ECG signal was given as the explanation. A kernel background cleaning-based technique for anomalous target detection was suggested [11]. The suggested method consists of two levels: kernel-based pure background pixel set extraction and background covariance matrix estimation using the returned pure background pixel set. Johnson et al. [12] employed ICA manipulation and hyperspectral imaging (HSI) anomaly detectors to locate anomalous pixels.

In this study, the yarn tension signal has been carried out by examining the system developed to detect the failures in the twister machine early. By using independent component analysis, noisy components in the yarn tension signal are separated without damaging the main component. Later on, anomaly detection has been made and defective regions in the yarn tension signal have been exposed. Ten different faulty yarn tension signals have been evaluated during the testing phase. The use of the ICA technique enhances the literature by allowing for predictive maintenance of yarn tension signals. When studies for predictive maintenance in textile machines are examined in the literature, this study is a new and unique study in terms of developing a method by examining yarn tension signals. In this study, by investigating the yarn tension levels through an ICA-based method, it is possible to determine whether or not there is an abnormal situation. In our study, the proposed method, as well as other techniques such as PCA, KPCA, SRP, and GRP, have been thoroughly evaluated in terms of precision-recall curve value and AUC value in the experimental results section.

2. Anomaly Detection

A simple definition of anomaly detection is a method that makes it possible to find unusual events or patterns in data. These unexpected events or patterns are genuine occurrences that deviate from the data's expected behavior. In the literature, these unanticipated events are referred to as outliers, exceptions, or anomalies. Data sets that do not fit a clearly defined pattern of typical behavior are considered anomalies [13]. Figure 2 shows anomalies in a straightforward 2D dataset. Two observation zones, N_1 and N_2, which each cover two regions, are present in the data. Far enough from the areas, the O_1, O_2, and O_3 points are oddities. Data irregularities can occur for a number of causes, including malware, credit card fraud, cyberattacks, or terrorist activities.

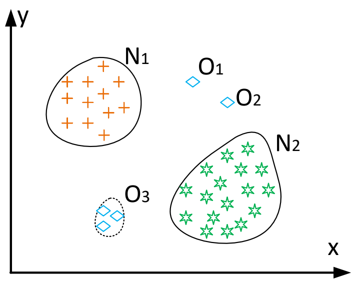


Figure 2. An illustration of an anomaly in a 2-D data set [14].

2.1. Difficulties of Anomaly Detection

It can be difficult to distinguish between typical and deviant behavior. Therefore, a neighboring anomalous observation can appear normal. Aggressive opponents frequently make adjustments to make abnormal observations seem normal when anomalies emerge from corrupt activity, making normal behavior even harder to identify. Most datasets do not frequently create clusters like the one in the previous example between normal and anomalous data. A cluster where the data is located may have a normal data anomaly nearby, and a cluster where the normal data is placed may have a normal data anomaly nearby. Anomaly detection becomes quite challenging in this situation.

Data or behaviors that we consider normal may alter over time. Therefore, it is not always easy to define what constitutes normal behavior. An anomaly detection method may not be applicable in all situations. In the medical area, a tiny change in body temperature, for instance, can signal abnormal conduct, whereas a small change in stock prices can signal normal behavior. This makes it impossible to use an anomaly detection method everywhere. It is important to do a rigorous operation to remove the noise in order to discover any noise abnormalities in the day-tastes (noise removal). However, separating noises is an extremely challenging procedure. It might be challenging to filter out and remove noise from data that frequently closely resembles true anomalies. The most common sort of anomaly detection problem is tough to fix as a result of the aforementioned issues. The majority of anomaly detection algorithms in use today can resolve a certain problem formulation. Figure 3 illustrates the aforementioned essential elements of any anomaly detection method.

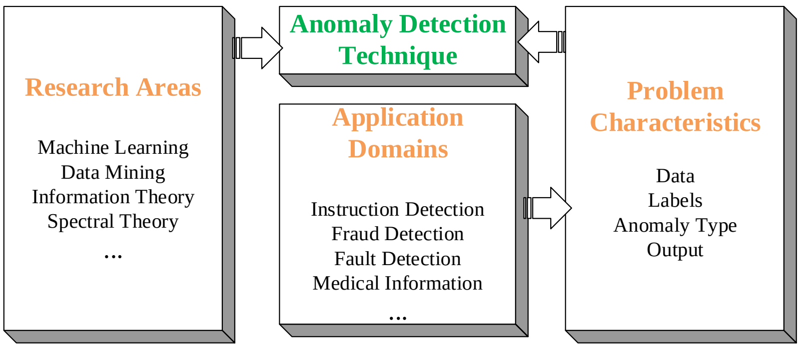


Figure 3. Anomaly detection's most important components

2.2. Types of Anomaly

A. Point Anomaly

If a data sample differs significantly from other normal data, it is considered anomalous data. Because the anomaly detection is dependent on a particular attribute, the cause of this anomaly detection is referred to as a point anomaly. For instance, we can look for irregularities in the amount we charge to our credit cards. For instance, in Figure 2, points O_1 and O_2 are not within the boundaries of the standard regions, nor are the points in the O_3 region, therefore the point anomalies are different from the usual data points.

B. Contextual Anomaly

A data sample behaves abnormally in a certain environment, which is known as a contextual anomaly or conditional anomaly. The dataset's structure makes it easier to understand the concept of context, which must be stated as part of the formulation of the problem. Three feature sets: environmental attributes, behavioral characteristics, define each data sample. In this illustration, the context is established using contextual attributes. The longitude and latitude of a point, for instance, are contextual elements in spatial databases. In time-series data, the contextual attribute of time reveals the direction of a row inside the overall row. Behavioral traits define a sample's non-contextual properties. Contextual features in spatial databases include, for instance, a position's longitude and latitude. In time-series data, time is a contextual information that specifies a row's position within a full row. Behavioral traits are used to categorize a sample's non-contextual properties. For instance, a behavioral feature in a geographic dataset that describes average precipitation worldwide is the amount of precipitation wherever. The context abnormality in the temperature time series t_2, t_1 is identical to the temperature at time t_2, but takes place in a different setting, therefore it is not regarded as abnormal [14]. Figure 4 is an example of temperature time series with a contextual anomaly.

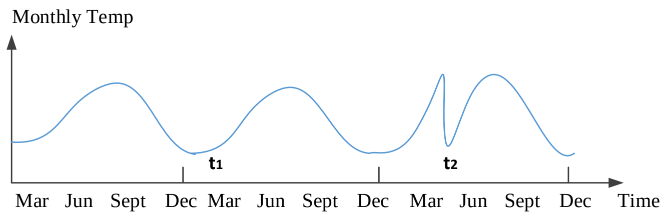


Figure 4. A temperature time series with a contextual anomaly.

C. Collective Anomaly

If the data connected to one another causes unusual behavior in the entire dataset, this is an illustration of a collective anomaly. When combined, certain connected data may create an anomaly, even though these data might not act in a single dataset. An illustration of a human ECG is shown in Figure 5. Because the same low value has been abnormally prevalent for a long period, the highlighted area displays abnormality.

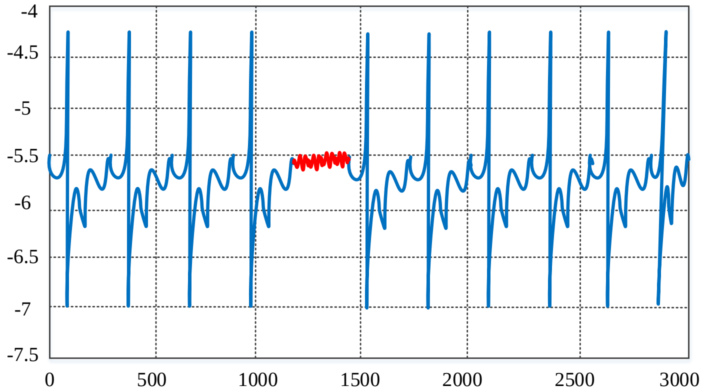


Figure 5. An example of collective anomaly [14]

3. The Proposed Method

By examining the yarn tension signals in the spinning machine, malfunctions in the twisting machine can be detected early. For some reason, the noisy signal can be added to the main thread tension signal. To analyze the yarn tension signal, the noise must be extracted from the main signal. By detecting anomalies in the signal obtained as a result of this process, it can be determined whether there is a malfunction. The ICA approach is used in the noise separation process.

3.1. Independent Component Analysis (ICA)

In 1988, Herault and Jutten [15] developed ICA for blind source separation (BBS). It's commonly used in voice, and medical signal analysis, as well as image processing [16]. In several scientific and engineering settings [17], an unknown mix matrix is assumed to linearly transform unobservable signals into a collection of observable mixed signals. Figure 6 and equation (1) denote the model.

$$X(t) = AS(t) + N(t) \tag{1}$$

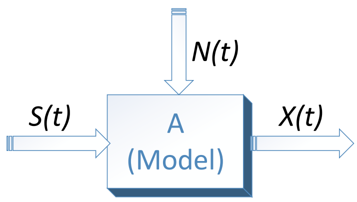


Figure 6. Mix system model [17]

In Figure 6, S(t) denotes unobservable source signals, 'A' means the mixing matrix, N(t) represents Gaussian white noise, and X(t) depicts the acquired data. The data variables in the model are assumed to be linear mixes of unseen source signals. They are referred to as the independent components of the observed data since they are non-Gaussian and mutually independent. When traditional approaches fail, ICA can expose these independent components or source signals [17]. It is quite beneficial to perform some pre-processing such as whitening and fixing before using an ICA algorithm [18-20]. With the assumption of the existence of M independent source signals $s = [s_1, s_2, s_3, \dots, s_M]^T$and observations of J mixture signal is $x = [x_1, x_2, x_3, \dots, x_J]^T$. The standard model of ICA is

$$x = A.s \tag{2}$$

In Equation (2), A is a JxM mixing matrix. The ICA's goal is to create a demixing matrix W that can be used to split the signal source vector into a set of statistically independent sources. Therefore, the independent components can be determined as

$$y = W.x \tag{3}$$

where y is the estimation of s. It can be seen from the Equation (2) and (3) that y is the linear combination of s [7].

$$y = Wx = WAs = Vs \tag{4}$$

In Equation (4), it is obtained V = WA. With ICA, it is aimed to find abnormalities in the signal after independent components are detected. In detecting an anomaly, a number of pre-processing steps are applied to the received input signal first. Thanks to this process, the properties of the signal are removed. Then anomaly detection is made and as a result, the time periods with abnormalities can be listed or the abnormalities can be removed from the main signal. Anomaly detection framework shows in Figure 7.

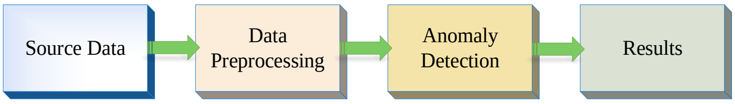


Figure 7. Anomaly detection framework

The proposed approach is completely data-driven and does not work based on threshold values. In this study, abnormalities were found by non-parametric Empirical Data Analytics (EDA) estimators, depending on the respective distribution of the data and the association characteristics. The proposed approach is completely data-driven and does not work based on threshold values. In this study, abnormalities were found by non-parametric EDA estimators, depending on the mutual distribution of the data and community characteristics. In the proposed study, potential anomalies were identified first, and these anomalies were divided into non-parametric data clouds. Later, abnormalities in each data cloud were determined. The proposed approach has been tested on ten separate yarn tension signals. Besides, the proposed approach has been compared with many methods such as Principal Component Analysis (PCA), Kernel PCA, Gaussian Random Projection (GRP), and Sparse Random Projection (SRP) to detect the components in the signal, and the highest precision and accuracy rate have been obtained in the proposed approach.

4. Experimental Results

In this study, yarn tension signals are taken as inputs, and the main signal is separated from the noisy components by the ICA method on these signals. Later, abnormalities in the signal have been detected. On the yarn tension signal, PCA, Kernel PCA, ICA, SRP and GRP methods are applied to separate the signal into its components, and the precision-recall curve and AUC (Area Under the Curve) curve of these methods are given below. In figure 8, there are examples of yarn tension signals. Figures of yarn tension and signal applied ICA are given in figure 9.

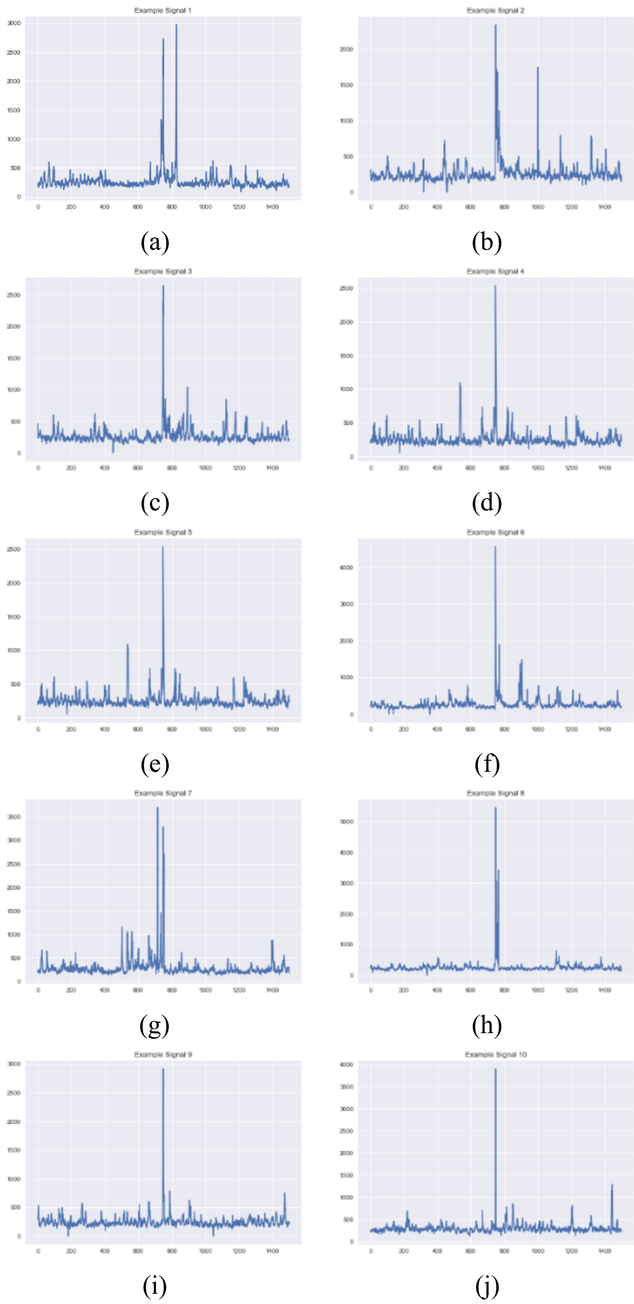
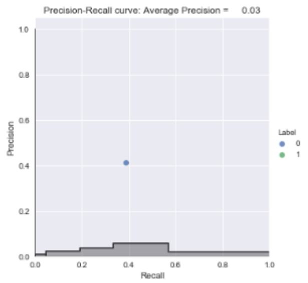


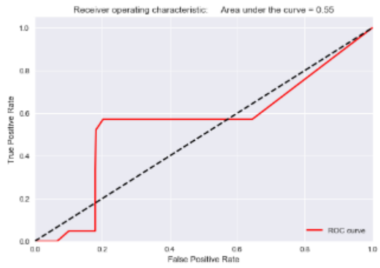
Figure 8. Examples of yarn tension signals.

(a)Yarn tension signal (b) ICA method applied

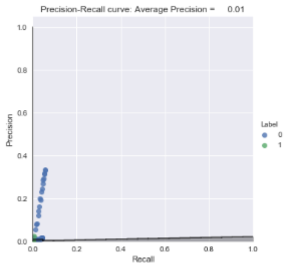
Figure 9. Yarn tension and signal applied ICA



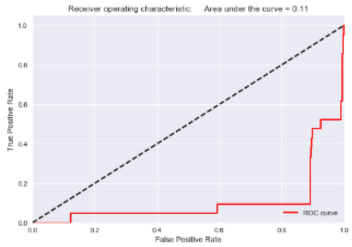
(a)Precision-recall curve of the PCA method



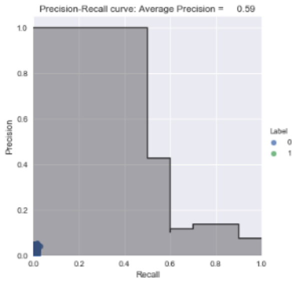
(b) AUC of the PCA method



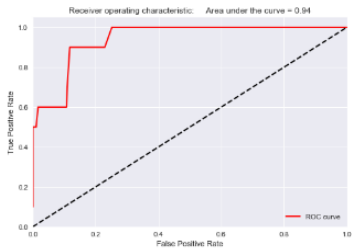
(c)Precision-recall curve of the Kernel PCA method



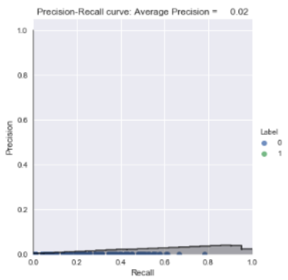
(d) AUC of the Kernel PCA method



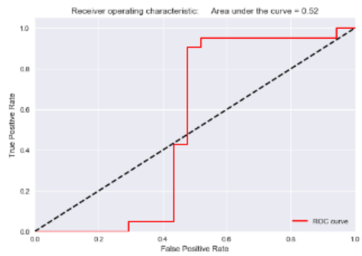
(e)Precision-recall curve of the ICA method



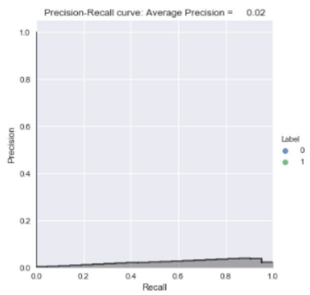
(f) AUC of the ICA method



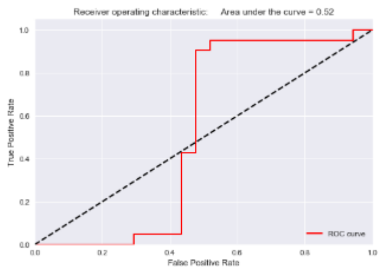
(g)Precision-recall curve of the SRP method



(h) AUC of the SRP method



(i)Precision-recall curve of the GRP method



(j) AUC of the GRP method

Figure 10. Precision-recall curves and AUC curves obtained from this study.

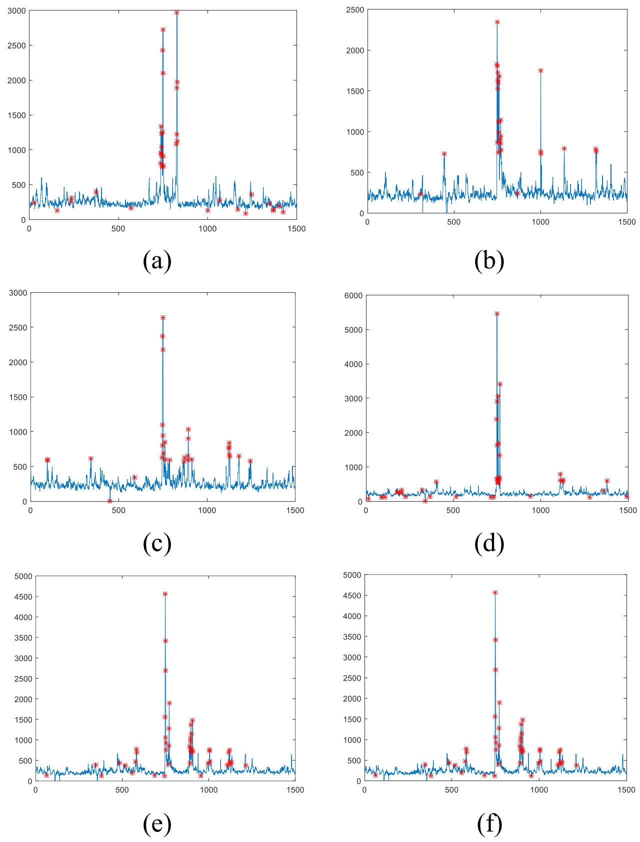


Figure 11. Anomaly detection results of example yarn tension signals

Table 1. Performance comparison of the proposed and other methods.

Method	Precision-recall curve value	AUC value
PCA	0.03	0.55
Kernel PCA	0.01	0.11
ICA	0.59	0.94
SRP	0.02	0.52
GRP	0.02	0.52

Anomaly detection results of example yarn tension signals are given in Figure 11. The drawback of the PCA method is that it ignores the less significant dimensions while examining the data. The PCA method is also computationally expensive for high-dimensional data. The KPCA method only captures nonlinear structures, although it uses less memory and processing resources than PCA. Size reduction is a task that both RP approaches must do, just like any other technique. Additionally, it provides the benefit of faster working speed. According to PCA, RP approaches do not demand that data be kept in memory. PCA performs best with data that has few dimensions. However, it may be claimed that with RP approaches, the quality degrades during the conversion process. It is considered that ICA multivariate data consists of the linear combination of a number of independent components. In most cases, it is assumed that the number of components equals the number of variables. It has a benefit because of this. When the data in Table 1 are evaluated, it becomes clear that the proposed ICA technique yields the best results. The performance in binary classification issues can be interpreted using the precision-recall curve and the AUC curve. The link between the genuine positive rate value and the positive predictive value is represented by the precision-recall curve. A low recall with high precision on the precision-recall curves denotes strong performance, while a high recall with low precision denotes subpar performance. This kind of analysis of the tables reveals that the suggested approach performs at the highest level. Precision-recall curves and AUC curves obtained from this study are given in Figure 10. On the other hand, this study also made use of the AUC curve, which is utilized to gauge a classifier's capacity for class distinction. The model performs better at differentiating between positive and negative classes the higher the AUC value. AUC value close to 1 indicates good distinguishability between classes. Figure 10 (f) indicates that the proposed method has the highest AUC.

5. Conclusions

The importance of anomaly detection is that the abnormalities in the data in various application areas turn into important information. When the yarn tension signals are examined, in cases where they defect for any reason, anomaly states are observed in these signals. Based on this difference, it can be determined beforehand whether there is a malfunction in the twister. Thus, a larger problem is prevented. Many methods are used in the literature to detect anomalies: cluster-based algorithms, statistical method algorithms, etc. In this study, using independent component analysis, the yarn tension signals in the twister machines have been examined and the defective signal regions have been determined. In this study, yarn tension signals are taken as inputs, and then the main signal is separated from the noisy components by the ICA method on these signals. Abnormalities in the signal have been detected. On the yarn tension signal, PCA, Kernel PCA, ICA, Sparse Random Projection (SRP), and Gaussian Random Projection (GRP) methods have been applied to separate the signal into its components, and results have been compared; it is observed that ICA produces more successful results than other methods.

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