International Journal of Engineering

A Statistical Method for Sequential Images–based Process Monitoring

M. A. Fattahzadeh, A. Saghaei*

Department of Industrial Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

A B S T R A C T

Today, with the growth of technology, monitoring processes by the use of video and satellite sensors have been more expanded, due to their rich and valuable information. Recently, some researchers have used sequential images for defect detection because a single image is not sufficient for process monitoring. In this paper, by adding the time dimension to the image-based process monitoring problem, we detect process changes (such as the changes in the size, location, speed, color, etc.). The temporal correlation between the images and the high dimensionality of the data make this a complex problem. To address this, using the sequential images, a statistical approach with RIDGE regression and a Q control chart is proposed to monitor the process. This method can be applied to color and gray images. To validate the proposed method, it was applied to a real case study and was compared to the best methods in literature. The obtained results showed that it was more effective in finding the changes.

doi: 10.5829/ije.2020.33.07a.15

NOMENCLATURE

T	Time	$\|.\|_2$	L_2 norm
N	Number of the in-control samples	r_t	Residual matrix at time t
B_t	Foreground image at time t (object image)	R_{new}	Vectorized form of r_t for new sample
$\hat{B}_t$	Predicted foreground image at time t	Q_{new}	Q-chart statistic
F	Transfer matrix	q	Degrees of freedom in χ^2 distribution
γ	Tuning parameter	p	The coefficient given to the Q-chart statistic

1. INTRODUCTION

Control chart, as a statistical tool, is widely used in monitoring quality characteristic(s) of a process or product. It was first introduced by Walter A. Shewhart in the 1920s. Shewhart used only one quality characteristic, such as length or weight, to monitor a process. Later, researchers developed multivariate models based on multiple characteristics. Woodall et al. [1] presented profile monitoring, which is used in many practical situations. Concurrently with the quality control methods, sensor technology, including image sensors, was developed. Process monitoring by these sensors has various applications in manufacturing processes, natural phenomena, medical decision-making, and sports activities. Many image-based methods have been developed for defect and fault detection [2–6]. However, some processes cannot be monitored by image-based methods, and we need to use sequential images. Of course, some researchers used sequential images but their purpose was only to detect faults in one image [7].

In this paper, we address sequential images–based process monitoring problem for processes that need more than one image. In this problem, the objective is to detect process changes that occur, for example, in the position, speed, shape, and color by using at least two images. Sequential images can be used in many contexts, e.g., in Welding (Figure 1a), Fabric texture (Figure 1b), Eddy phenomenon (Figure 1c), and Solar flare (Figure 1d) [7–9].

This problem has complex characteristics, including 1) high dimensionality, where some sequential images

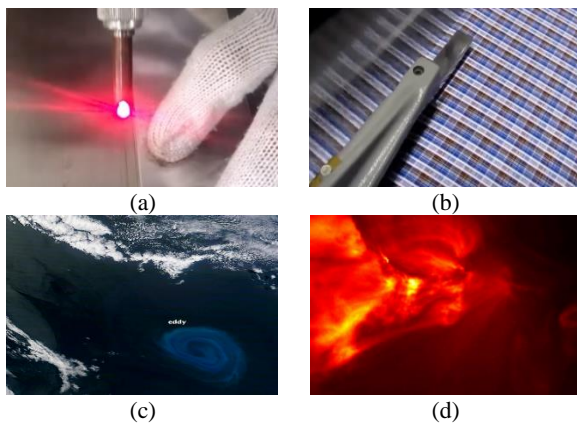*Corresponding Author Email: a.saghaei@srbiau.ac.ir (A. Saghaei)

Figure 1. Applications of the sequential images-based processes; a) Welding and laser welding, b) Fabric texture, c) Eddy phenomenon (Image courtesy of the NASA Earth Observatory), d) Solar flare

are at least 0.5M pixels; 2) the correlation between the images; 3) spatial and temporal structure: pixels are spatially correlated within an image and, most of the time, are temporally correlated across the sequential images [7].

Our proposed methodology, inspired by data stream monitoring [7], can handle both grayscale and color images. We present a new method that predicts the behavior of objects in the next image and uses the prediction error to monitor the shape, color, and speed changes of objects.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 introduces the proposed method. In Section 4, we illustrate and evaluate how our proposed method can find changes in a real case. In Section 5, the paper is concluded and some future research areas are provided.

2. LITERATURE REVIEW

In this paper, a common procedure in machine-vision systems [10] is used to monitor the changes in the sequential images. In this procedure, first, image data are collected by the corresponding sensor. Then, the data are preprocessed, by background removal, compressing, denoising, etc.. After that, a set of monitoring features are extracted from each image. Finally, the extracted features are monitored by statistical or engineering methods.

Zou et al. [11] developed a powerful method for monitoring independent data streams. They assumed that the data streams were independent, and therefore, ignored their spatial and temporal structures. The monitoring of data streams with a temporal trend was addressed by Xiang et al. [12], and Qiu and Xiang [13]. They used nonparametric regression with longitudinal techniques. However, they did not address the spatial

structure. Yan et al. [7] proposed a novel methodology based on spatio-temporal decomposition for data streams monitoring. Using the lasso method, the image and profile were decomposed to the functional mean, sparse anomalies, and random noises. For the validation of this method, solar activity and steel rolling process were used. They detected the defects in the process, seams in the process of steel rolling, and flares in solar activities. Bračun and Sluga [8] used a stereo monitor for the welding track sensing system. They measured the position of the arc in the 3D space and in the time sequence. They used two high-speed cameras, calculated the center of the arc, and finally saved the direction of motion. Similar to Yan et al. [7], they addressed defect anomalies. This method was designed only for the welding path and is inefficient for other processes. Faghmous et al. [9] provided a parameter-free spatio-temporal model for the detection and trace of an eddy in an ocean. This method was based on finding extreme points in the neighborhood.

For monitoring simple multivariate problems, multiple methods such as T^2, Q-chart, MCUSUM, EWMA, etc. [14–17] can be used. But according to Megahed et al. [18], for monitoring matrix or tensor data like image and satellite data, the monitoring methods are divided into several groups including profile-based and multivariate techniques, multivariate image analysis (MIA) control charts, and spatial control charts.

In the first group, multivariate control charts are used with a feature extraction method. For example, Wang and Tsung [19] modeled the relationship between a baseline and a sampled image using Q-Q plots and used profile-monitoring for changes detection. However, in their method, the information about pixel locations was ignored. In MIA, the features of each color channel were extracted by using partial least squares regression or principal component analysis (PCA). Yan et al. [3] used Low-Rank Tensor Decomposition (LRTD) for monitoring an image-based process. They used multi-linear PCA (MPCA) to extract features and proposed a combined control chart, based on T^2 and Q charts.

The spatial control charts use non-overlapping windows. These windows move across an image to obtain spatial information [20]. Jiang et al. [21] used ANOVA technique for spatial monitoring of the LCD panels and exponentially weighted moving average (EWMA) control chart for detecting the defects in grayscale images.

Some processes are not static and have specific movements. For example, in the fabric weaving process, if the production speed changes or even if the machine is stopped, it can affect the quality of the produced fabric. Image-based methods cannot detect these changes because they monitor the process using only one image. They cannot detect factors such as changes in speed or pattern because they do not pay attention to the time dimension.

The main contribution of this paper is the adding of the time dimension to image-based process monitoring and developing sequential images-based methods for detecting process changes. This can, in addition to the changes in shape and color, detect the changes in the movement pattern such its speed, acceleration, and direction. So, we propose a general statistical method with ridge regression applying previous images in monitoring. A real case study is proposed to evaluate the performance of the proposed method. Also, we compared the proposed method with some image-based methods in literature. Besides the mentioned applications in Figure 1, the sequential images-based process monitoring has various applications, including manufacturing (such as glass forming, steel rolling), traffic control (such as identifying high-risk behaviors), food industries (such as bread baking), and etc.

3. PROPOSED METHOD

An overview of the proposed method is shown in Figure 2. It consists of four steps. The first step is image acquisition, in which the input data as the sequential images are required to be divided into separate images. The next step is the data preprocessing, where first the background is removed and then if the image is noisy, the noise is removed. Step three is feature extraction, in which we estimate a transfer matrix that can predict the next image. The differences between the predicted image and the actual image constitute the residuals matrix. In the final step, these residuals are monitored by the multivariate control charts.

The proposed method has several variables and parameters, shown in Nomenclature.

3. 1. Image Acquisition
In this problem, the input data is in the form of sequential images. Therefore, they must be separated without changing the sequence of the images.

3. 2. Preprocessing
The images obtained from the previous step consists of two parts: the foreground (or object) and the background. The background should be removed and only the foreground be remain because the aim is the monitoring of the object changes. The selection of the algorithm we should use for the background removal depends on many factors, such as the data type, whether the background is dynamic or static, whether it is smooth or non-smooth, whether the camera is fixed or not, etc. For example, for removing a static background captured with a fixed camera, background subtraction is a suitable method.

Sometimes the images after the background removal are noisy. This noise should be eliminated. Several methods can be used for this, such as median filtering and Gaussian smoothing. See [22] for more details about the

noise and noise removal. The obtained foreground image after denoising at time t is denoted by B_t.

3. 3. Feature Extraction
In this step, it is assumed that N in-control samples are available and each foreground image at time $t + 1$ (B_{t+1}) can be predicted by the previous foreground image (B_t). Although more previous images can be used for prediction, but for simplicity, only the latest one is used. The predicted foreground image at time $t + 1$ is denoted by $\hat{B}_{t+1}$, which can be used by Equation (1).

$$\hat{B}_{t+1} = B_t \times F \tag{1}$$

To calculate $\hat{B}_{t+1}$ using B_t, we need a transfer matrix, illustrated by F. In Equation (2), γ and $\|.\|_2$ denotes respectively the tuning parameter and L_2 norm. This transfer matrix is estimated by N sequential in-control samples.

$$argmin_{F_t} \sum_{t=1}^{N-1} \left\| \hat{B}_{t+1} - B_{t+1} \right\|_2^2 + \gamma \|F\|_2 \tag{2}$$

This equation is a ridge formulation. Since both parts of Equation (2) are differentiable, we use differentiation to optimize this equation. Thus, F could be optimized by Equation (3). In Equation (3), I is defined as the identity matrix.

$$F = \left(\sum_{z=1}^{N-1} B_{t,z} * B_{t,z}{}^T + \gamma I \right)^{-1} \sum_{z=1}^{N-1} B_{t,z} * B_{t+1,z} \tag{3}$$

The residuals as the difference between the actual and predicted images are obtained by Equation (4) for all images. Let's define r_t as a residual matrix.

$$r_t = B_t - \hat{B}_t \qquad \forall\, t = 2, 3, \dots, N \tag{4}$$

3. 4. Monitoring
The in-control samples are used to calculate the transfer matrix and control limits. Here, we use the Q-chart for monitoring the residuals. The Q-chart statistic is based on the residual matrix obtained from Equation (4).

For each new sample, the estimated transfer matrix is used for the calculation of the residuals and plotting the monitoring statistic on the designed Q-chart.

The residual vector of the new sample is represented by $R_{new} = vec(r_t)$. The Q-chart statistic (Q_{new}) is obtained using Equation (5).

$$Q_{new} = \|R_{new}\|_2^2 \tag{5}$$

The residuals are assumed to follow a multivariate normal distribution, and therefore Q_{new}/p follows a χ_q^2 distribution, where q denotes the degrees of freedom and p is the coefficient given to the statistic to follow the known distribution function χ_q^2. The parameters p and q can be estimated by the moments method [23]. They can be obtained by solving Equations (6) and (7).

$$E(Q_{new}) = pq \tag{6}$$
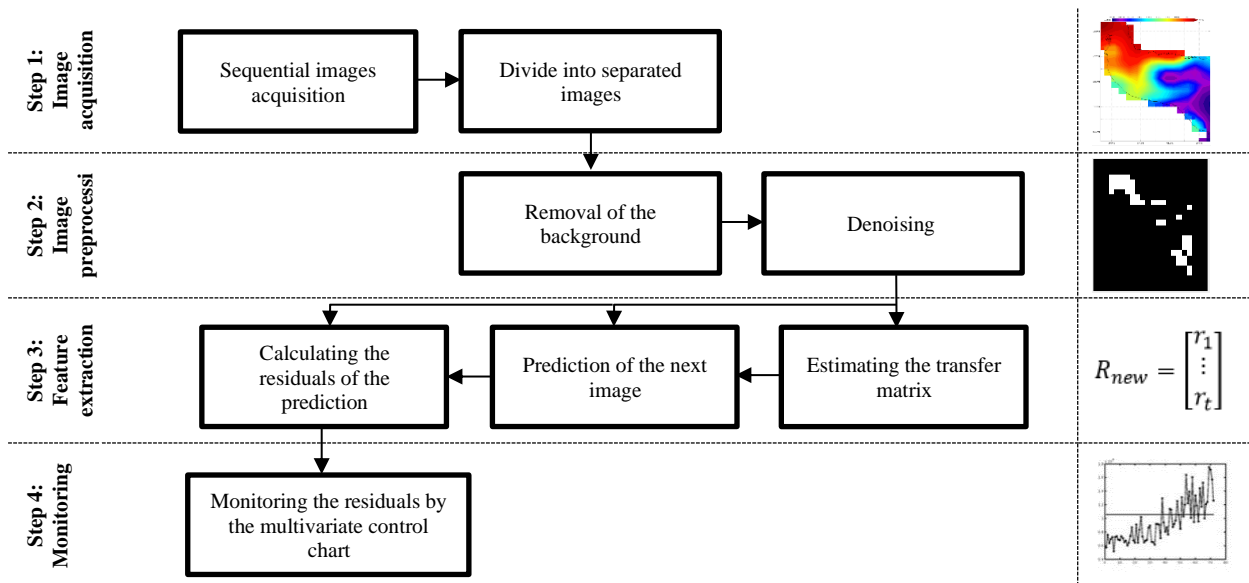
$$Var(Q_{new}) = 2qp^2 \tag{7}$$

Figure 2. The overview of proposed method

The Q-chart control limit can be calculated by $(1 - \alpha)\%$ of the χ^2 distribution with q degrees of freedom.

4. CASE STUDY

4. 1. Case Description   Mesoscale eddies are coherent rotating vortices of water with a span of 25–250 kilometers (Figure 3) lasting 10 to 100 days [9]. Eddies are critical phenomena with an important role in dominating the ocean's kinetic energy. They are responsible for the transport and mixing of heat, salt, nutrients, and energy across an ocean or sea [24]. Moreover, they have a significant impact on terrestrial and marine ecosystems [25]. The creation or growth of eddy provides a large amount of food for phytoplankton and provides them with growth opportunity. This can cause serious damage to the region's ecosystem, such as massive aquatic mortality. Moreover, it can stop tourism activities in the region. In this case, the growth of phytoplankton must be counteracted. For example, coral reefs were destroyed over seven thousand years due to the high growth of phytoplankton, enhanced by an eddy [26]. Eddy changes are urgently needed to be discovered because phytoplankton populations impose damage to the ecosystem and make changes in water flows, which transmit pollution and sea anomalies damaging the maritime tourism industry.

Thus, in this paper, to validate the proposed method, the eddies in the Oman Sea are monitored and unusual behaviors of eddy properties are detected. Position, velocity, size, and height are defined as eddy properties [27].

4. 2. Implementing the Proposed Method
4. 2. 1. Image Acquisition   In step (1), the input data are converted to separate sequential images. We use satellite data from the AVISO dataset. This dataset is publicly   available   online   at https://las.aviso.altimetry.fr/las/UI.vm. In this dataset, Latitude and Longitude of the Oman Sea specified by 22° to 27° and 56° to 60° respectively, on a 0.25° (~28km) grid. These data are weekly sequential matrices with a size of 20×16 pixels collected from 1993/01/01 to 2018/12/31. Thus, we need to separate them without disrupting their order.

The value of each pixel represents the sea surface height (SSH) in meter. A sample of 25 years, consisting of 1357 weeks, is used and the first 3 years are considered as the in-control sample.

Most of the time, SSH data are reported as a vector, so we need to reshape them into a rectangle.
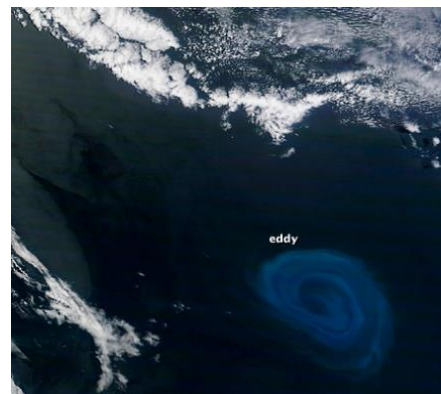

Figure 3. A mesoscale eddy

4. 2. 2. Preprocessing   In step (2), the data is preprocessed for further analysis. The output of the previous step is illustrated in Figure 4.

Here, we need to separate the foreground from the background, where eddies are our foreground, required to be monitored. One of the best methods for separating eddies from the background is the method introduced by Faghmous et al. [9]. Figure 5 illustrates the eddies extracted from the image shown in Figure 4. The outputs of this algorithm are not noisy, so we do not need any denoising.

4. 2. 3. Feature Extraction   The main objective in step 3 is the estimation of the transfer matrices. It is assumed here that eddies behavior is independent in each month. Therefore, one transfer matrix should be calculated for each month (i.e., a transfer matrix is used to predict the images of each month) and one transfer matrix should be calculated for when the month changes, to predict the first week of the new month (this is due to seasonal changes). Therefore, we need to find 24 transfer matrices, which are of two types; Type I: transfer matrices for each month of the year (totally, 12 transfer matrices), and Type II: transfer matrices for when the month changes (totally, 12 transfer matrices). To estimate these transfer matrices, Equation (2) is made by $\gamma = 0.01$ and 3 sets of $N = 4$ in-control samples for Type I (for example, for estimating transfer matrix of April, we use the weekly data of the Aprils in the three in-control years), and 3 sets of $N = 2$ in-control samples for Type II.

When the prediction of the eddy matrix is obtained, the difference between the actual images and the predictions constitutes the residual matrix.

4. 2. 4. Monitoring   In step 4, we encounter two different sample sizes, each of which requires two control charts. The in-control samples are used to calculate the control limits of the Q-charts. Then, for each new sample, first, the transfer matrix is selected, then the residuals are calculated, and finally, the statistic is calculated and plotted on the Q-chart.
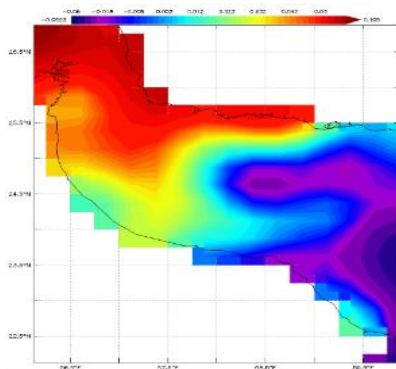

Figure 4. The original image 2008/09/01

Figure 5. Extracted eddies from the original image 2008/09/01

The control charts for both types are shown in Figure 6. In these two control charts, only the data for the in-control years and two new years (2007 and 2014) are shown. The complete control charts (from 1993 to 2018) are available at bit.ly/2pqZlhi.

4. 3. The Proposed Method Results   To evaluate the performance of the proposed method, we examine some of the storms that occurred at that time. One of the out-of-control samples is 2007/06/04. This out-of-control state was caused by the Gonu storm. This storm entered Iran at 2007/06/04 and the control chart detected an out-of-control sample at exactly the same date. The large quantities in the future weeks were due to the storm.

Out-of-control samples were observed in 2014/06/16 and 2014/06/23, which were occurred due to the Nanauk storm. It was started at 2014/06/10, one day after the last day the satellite recorded its information. Regarding the weekly structure of the data, the proposed method was able to correctly identify the out-of-controlled state.

The Nilofar Storm, which began operating in the Arabian Sea at 2014/10/25 towards the Oman Sea, was active until the 2014/10/31. The control charts discovered the first out-of-control sample on 2014/11/03 and the Nilofar Storm may be the reason for other out-of-control states in the coming weeks.

In Table 1, all storms of the Oman Sea and important storms in the west of the Arabian Sea with speed more than 100 km/h in peak time are indexed because it is assumed that these storms can affect the Oman Sea eddies. The proposed method discovered all storms in the Oman Sea and in the north and middle of the Arabian Sea. Also, it discovered most of the storms in the south of the Arabian Sea.

4. 4. Comparison Study   To demonstrate the performance of the proposed method, some statistical feature extraction methods, kernel-PCA (KPCA) and PCA, are applied. To monitor the extracted features of PCA and KPCA methods, the T^2 control chart is used. Also, based on our best knowledge, the LRTD method [18] is the most powerful method that can accurately detect the smallest changes in the images, considering the
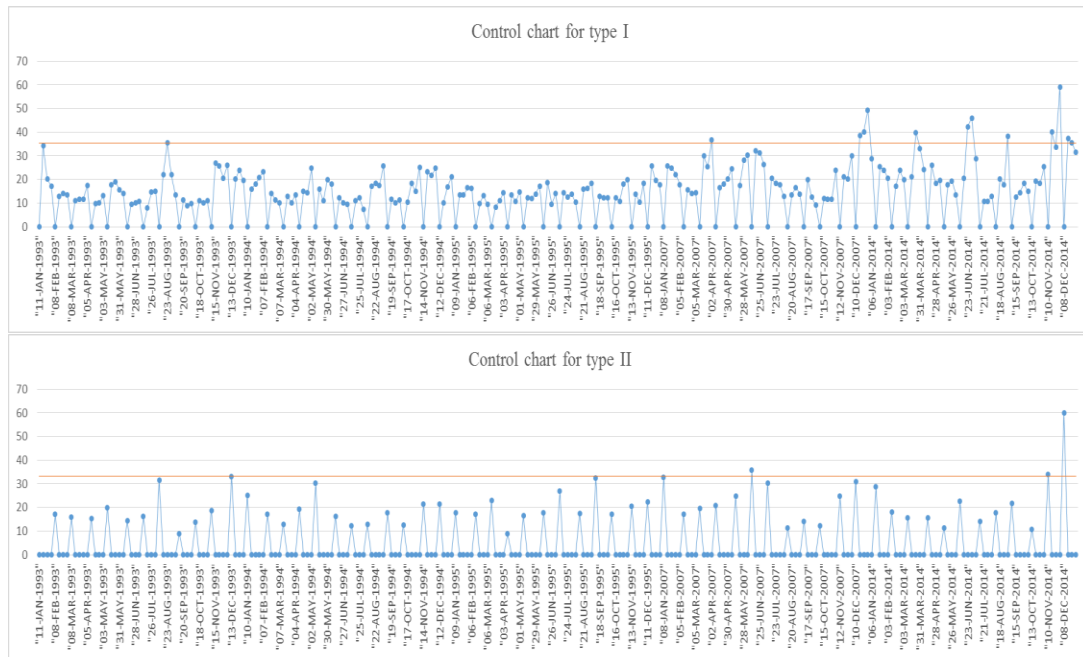
Figure 6. Q control charts for eddy monitoring (Type I and Type II)

seasonal effects. The reason why we use these image-based methods in this comparison study is that the existing sequential image-based methods have been designed either for a specific process or for fault detection in images. Therefore, we cannot use these methods.

As shown in Table 1, twelve major storms occurred in the specified time and place. Among the methods used for comparison, the results of PCA and KPCA methods are very weak and identified less than 6 cases. The LRTD method performed relatively well and identified 8 cases,

while the proposed method was able to identify 10 out of the twelve cases, representing its better performance.

The reason why these methods, and even the LRTD method which is a powerful method, performed worse than the proposed method, is that these methods have not considered the time dimension. Ignoring the time dimension in the monitoring of eddies leads to the loss of eddies motion information. Eddies can move, rotate, be resized, and have a variable height over time, and neglecting this information causes that time-dependent changes do not be identified correctly.

TABLE 1. Storms in the Oman Sea and important storms near the Oman Sea

Year	Date	Speed in Peak (km/h)	Place	Proposed method	LRTD	KPCA-T^2	PCA-T^2
1998	11 - 17 DEC	100	Middle of the Arabian Sea	☐	☐	☐	✗
2007	1 – 7 JUN	235	The Oman Sea	☐	☐	☐	✗
2010	30 MAY – 7 JUN	155	The Oman Sea	☐	☐	☐	☐
2014	10 – 14 JUN	85	North of the Arabian Sea	☐	☐	✗	✗
2014	25 – 31 OCT	205	North of the Arabian Sea	☐	✗	✗	☐
2015	7 – 12 JUN	85	North of the Arabian Sea	☐	☐	✗	✗
2015	28 OCT – 4 NOV	215	South of the Arabian Sea	☐	☐	☐	☐
2015	5 – 10 NOV	175	South of the Arabian Sea	☐	☐	☐	✗
2016	6 - 18 DEC	130	South of the Arabian Sea	☐	✗	✗	✗
2018	21 – 27 MAY	175	South of the Arabian Sea	✗	✗	✗	✗
2018	6 – 15 OCT	140	South of the Arabian Sea	✗	✗	✗	☐
2018	10 – 20 NOV	110	South of the Arabian Sea	☐	☐	✗	✗

5. CONCLUSION

Image data are being increasingly used for monitoring different processes, such as manufacturing ones. Some processes are not static and have motion patterns. So, they cannot be monitored with a single image. For the image analysis of non-static processes and detecting changes such as speed, acceleration, and direction, adding time dimension and considering sequential images is essential and improves the results. On the other hand, the temporal correlation between the images, made by adding the time dimension, requires new analytical methods that can handle this correlation and provide better results than the image-based methods.

In this paper, we proposed a novel method combining RIDGE regression and multivariate control chart for sequential image–based process monitoring. In the proposed method, the features are extracted by a statistical method using RIDGE modeling and then the Q control chart is utilized for the monitoring of the residuals. We applied the proposed method to a case study, where the changes in the Oman Sea eddies made by storms were monitored and out-of-control samples were discussed. The proposed method was compared with the LRTD, KPCA, and PCA methods and the results showed that the proposed method, because of considering the time dimension and temporal effect between the images, performed better than the image-based methods and was able to detect more variations.

One important and challenging research topic that needs further study is finding the root cause of out-of-control samples and identifying their underlying factors, including the shape, number, and position of objects. Also, for simplicity, we considered only one previous image for prediction, which can be extended by considering more previous images.

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Persian Abstract

چکیده

امروزه با رشد تکنولوژی، پایش فرآیندها با بکارگیری سنسورهای تصویری و ماهواره‌ای به دلیل اطلاعات غنی و ارزشمند، گسترش پیدا کرده است. به تازگی برخی محققان برای کشف عیوب در تصویر، از تصاویر متوالی استفاده کرده‌اند، چرا که تحلیل فرآیند به صورت مستقل و با استفاده از یک تصویر امکان‌پذیر نیست. این مقاله با افزودن بعد زمان به مسئله پایش فرآیند به کشف تغییرات حالت فرآیند (مانند اندازه، محل، سرعت، رنگ و ...) می‌پردازد. همبستگی زمانی بین تصویرها و ابعاد بالای داده‌ها باعث شده که این مسئله یک مسئله پیچیده محسوب شود. در این مقاله یک روش آماری با رویکرد مدل‌سازی رگرسیون تیغه‌ای و نمودار کنترل Q برای پایش فرآیند بر پایه تصاویر متوالی پیشنهاد شده است. این روش می‌تواند در تصاویر رنگی و خاکستری بکار برده شود. برای اعتبارسنجی مدل یک مثال واقعی استفاده شده است و عملکرد آن با بهترین روش‌های موجود در ادبیات موضوع مقایسه شده است. نتایج حاصله نشان داد که روش پیشنهادی از اثربخشی بیشتری برخوردار بوده و توانسته تغییرات بیشتری را شناسایی نماید.