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An Online Detection Method for Identifying True Change Points

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Abstract. Time series data can be analysed using the singular spectrum analysis (SSA) technique by decomposing the data into its most basic elements, such as trends, recurrent patterns, and noise. Change point detection, a sequential application of SSA, is a procedure that uncovers the locations in time series data when sudden changes in its attributes occur. In an offline setting, the objective is to detect change points by analyzing the full dataset simultaneously. On the other hand, in an online (sequential) setting, the goal is to detect changes as fast as feasible using streaming data points. In this study, a novel online change point detection algorithm is proposed, which uniquely combines a sequential application of SSA with an integrated alarm mechanism. This combination allows for real-time detection while explicitly differentiating between genuine changes (true alarms) and fake changes (false alarms). Several Experiments are performed in MATLAB and it is found that the window width parameter N is essential for detection procedure. The selection of the appropriate parameter is critical to guaranty accurate online change point detection. Since extremely small values of N cause false detections by mistaking outliers for change points, whereas exceptionally large values of N frequently miss true change points. Thus, the best value of N for striking a balance between sensitivity and accuracy is either medium-sized or large. The study concludes that the newly developed SSA-based algorithm handles both synthetic and real-world data, offering a reliable tool for real time data analysis with a low number of false alarms and precise detection of notable changes.

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1. Introduction

Singular Spectrum Analysis (SSA) is a versatile tool for extracting seasonal components, multi-resolution trends, smoothing, identifying cycles with varying periods, uncovering intricate patterns, analyz-ing short time series, and detecting change points. Change Point Detection is one of the SSA's applications. In time series analysis, change point detection identifies structural shifts caused by specific events. Offline detection exam-ines the entire dataset at once [16], while online (or sequential) detection aims to promptly detect changes using streaming data [11].

The basic or offline change-point detection algorithm operates under the hypothesis that if the mechanism generating the time series $x(t)$ has changed at a certain time moment τ, then an increase of difference between a subspace of R^M by specific eigenvectors of the lag covariance matrix, and $M-$lagged vectors $(x_{j+1}, ..., x_{j+M})$ are expected for $j \geq \tau$. In other words, offline scenario is based on applying SSA successively to subseries of the original series while keeping an eye on the accuracy of the approximations of the remaining portions of the series by appropriate approximations [10]. SSA and change-point detection are model-free techniques useful for building flexible models across various fields, including speech recognition, image analysis, environmental monitoring, and medical status tracking.

This research uses Singular Spectrum Analysis (SSA) to develop an online change point detection (OCPD) algorithm capable of detecting significant data pattern changes in real time. The SSA-based method will be tested on synthetic periodic data and real-world datasets, like EMG, to evaluate its performance, optimize accuracy, and address domain-specific concerns.

The concepts of SSA were independently developed in Russia [18] using singular value decomposition (SVD). Although repeated QR updating algorithm [22] and eigenvalue methods are present in literature [3], SVD outperforms the decomposition in SSA. A number of groups in UK and USA worked on SSA discussing its methodological features and uses [17].

Change point detection (CPD) detects major changes in a system's temporal evolution within noisy observations. This task has gained popularity in the statistics and machine learning areas through its diverse uses, including quality control [13], climate research [6], medical status monitoring [7], image analysis [5] and speech recognition [12]. CPD detects rapid changes in the data when a time series property changes [9]. Segmentation, edge detection, event detection, anomaly detection, Active contours detection for single and multiple Object Extraction [14], and change point detection are all related concepts that are occasionally used. Change point detection is related to the well-known issue of change point estimates or mining [4].

Baranowski et al. presented a multiple change-point detection device known as Narrowest-Over-Threshold (NOT) to focus on the narrowest segment among those whose contrast surpasses a predetermined threshold [2]. Yu et al. discussed a two-step technique for detecting multiple change points in piecewise polynomials with general degree [21]. Anastasiou and Fryzlewicz offered the Isolate-Detect (ID) technique to search for changes in expanding data segments [1]. The comprehensive study of change point detection techniques has been discussed in Truong et. al. [16].

The distinction between CPD approaches is whether they are online or offline. In an offline case, the dataset is fixed, and detection is done retroactively based on the full d ataset. In such cases, the only concern is the detection accuracy. On the other hand, in an online case, decisions must be taken rapidly as data is received in a sequential manner. In addition to detection accuracy, the number of data points observed after the change until it is identified, or the detection delay, is another crucial parameter in the online setting. Wald began the statistical exploration of online change point detection problems as an introduction to sequential analysis [19]. Xie et al. provided a comprehensive survey of the extensions and modern applications of sequential change-point detection [20]. The online change-point detection (CPD) problem is commonly addressed through sequential hypothesis testing, where a linear combination of binary hypothesis tests is applied to incoming observations [15]. This framework enables a principled evaluation of online CPD methods by characterizing their performance in terms of the fundamental trade-off between false alarm rate and detection delay.

The primary novelty of the proposed work is threefold. First, it introduces a fully sequential adaptation of Singular Spectrum Analysis suitable for real-time processing. Second, it embeds a dedicated alarm mechanism capable of distinguishing persistent structural changes from transient noise, addressing a key challenge in real-world streaming scenarios. Third, the proposed method is evaluated on both synthetic and real-world datasets, demonstrating its robustness and practical utility across diverse applications.

This paper is organized as the Section 1 of the proposed work provides an introduction and liter-ature survey, followed by the methodology of SSA in Section 2, including embedding and reconstruction, and demonstrates application with an example dataset. Section 3 details the methodology for real-time change point detection, analyzing two cases: without alarms and with alarms. The experimental results are given in section 4 while section 5 provides the conclusion.

2. Singular Spectrum Analysis and its Application

2.1. **The SSA Algorithm.** The singular spectrum analysis is performed in two steps: first decomposition and then reconstruction. In the initial stage, the series is decomposed, while in the subsequent stage, the original series is reconstructed. The reconstructed series, free from noise, is used to foresee new data points. The SSA algorithm is summarized in Algorithm 1.

SSA analyzes the structure of time series data in a non sequential (offline) manner. However, change-point detection usually entails a sequential (online) approach. Our goal is to create an algorithm suitable for deployment in an on-line setting. Some prominent features of the SSA that make it suitable for online data analysis are its ability to:

Algorithm 1 Singular Spectrum Analysis (SSA)

1: **Input**: Time series $\{x_1, x_2, \cdots, x_N\}$, lag parameter $M \leq \frac{N}{2}$
2: **Stage 1: Decomposition**
- **Step 1: Embedding**
- Construct trajectory matrix $X = (x_{ij})_{i,j=1}^{M,K}$ with $K = N - M + 1$
- **Step 2: Singular Value Decomposition (SVD)**
- Compute lag covariance matrix $S = XX^T$
- Determine eigenvalues λ_i and eigenvectors U_i of S
- Decompose X using eigentriples into $X = X_1 + X_2 + \cdots + X_d$, where $X_i = \sqrt{\lambda_i} U_i V_i^T$

3: **Stage 2: Reconstruction**
- **Step 1: Eigentriple Grouping**
- Group indices $\{1, 2, \cdots, d\}$ into q subsets $I_1, I_2, \cdots, I_q$ and group corresponding matrices to form new matrices X_{I_j}.
- **Step 2: Diagonal Averaging**
- Convert each matrix X_{I_j} into a new series through diagonal averaging to produce a reconstructed series
- Sum reconstructed series to approximate the original series

4: **Output**: Decomposed and reconstructed time series $\{\tilde{x}_n^{(1)}, \cdots, \tilde{x}_n^{(q)}\}$

- decompose incoming data into trends, oscillations, and noise, enabling real-time analysis of adaptive structures,
- update the trajectory matrix and lag-covariance matrix as new data points arrive, ensuring continuous monitoring of a sliding window approach,
- detect changes in the eigenvalues or subspaces dynamically to reflect shifts in data patterns,
- filter noise and improve the accuracy of detection and hence reduction of false alarms,
- not rely on predefined models and remain versatile across different types of datasets and scenarios,
- ensure reliable identification of true change points by focusing on key components of the data.

3. An Online Change Point Detection

In an online change point detection (OCPD), data is adaptive. this process, it takes new data and keeps on detecting it.

Instead of applying SVD to the trajectory matrix for $[1, N]$, we apply it to the trajectory matrix calculated in the time interval $[n + 1, n + N]$ of length N for each time n. The change-point detection technique is therefore, made sequential and makes it possible to adapt to a slow shift in the time series structure, outliers, and multiple changes. The iteration number in this case is n, and the duration of the time period used to generate the trajectory matrix is N. Algorithm 2 summarizes the main steps of the proposed OCPD algorithm.

Algorithm 2 Online Change-Point Detection (OCPD)

Input: Time series data $x_1, x_2, \ldots$, parameters N, M, l, p, q, threshold H **Initialize:** For $n \geq 0$, time interval $[n+1, n+N]$, set $K = N - M + 1$

while new data is available **do**

- **Step 1:** Construct initial trajectory matrix $X_B^{(n)}$:

$$X_B^{(n)} = \begin{pmatrix} x_{n+1} & x_{n+2} & \cdots & x_{n+K} \\ x_{n+2} & x_{n+3} & \cdots & x_{n+K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n+M} & x_{n+M+1} & \cdots & x_{n+N} \end{pmatrix}$$

  Update incrementally by shifting columns and adding the new data point.
- **Step 2:** Compute the lag-covariance matrix:

$$R_n = X_B^{(n)} (X_B^{(n)})^T$$

  Update incrementally using the new base matrix.
- **Step 3:** Perform SVD on R_n to obtain M eigenvalues and eigenvectors.
- Select l eigenvectors to form subspace $\mathcal{L}_{n,I}$.
- **Step 4:** Compute detection statistics:
- **for** $j = p + 1$ to q **do**

$$\mathcal{D}_{n,I,p,q} = \sum_{j=p+1}^{q} \left[(X_j^{(n)})^T X_j^{(n)} - (X_j^{(n)})^T U U^T X_j^{(n)} \right]$$

- **end for**
- **Step 5:** Normalize the detection statistics:

$$\tilde{\mathcal{D}}_{n,I,p,q} = \frac{1}{M(q-p)} \mathcal{D}_{n,I,p,q}$$

- **Step 6:** Estimate υ_n:

$$\upsilon_n = \begin{cases} \tilde{\mathcal{D}}_{n,I,p,q}, & \text{if } n = 0 \\ \upsilon_{n-1}, & \text{otherwise} \end{cases}$$

- **Step 7:** Compute the normalized statistics:

$$S_n = \frac{\tilde{\mathcal{D}}_{n,I,p,q}}{\upsilon_n}$$

- **Step 8:** Detect change point:
- **if** $S_n \geq H$ and $n > \frac{N}{2}$ **then** Change point detected at $\bar{\tau} = \bar{n} + q + M - 1$
- **end if**
- Increment n
- **end while**

Output: First detected change point $\bar{\tau}$, or return **None** if no change point is detected.

3.1. **Theoretical Analysis.** At each time step, the OCPD algorithm embeds the most recent observations into a trajectory matrix, performs an incremental singular value update, and compares the evolving signal subspace with its historical structure to detect anomalies. Exact SSA updates require cubic time with respect to window length due to repeated decompositions, making them suitable only for moderate window sizes, while fast or incremental SSA variants reduce this to quadratic or near-linear time through rank-one updates and partial decompositions. The method provides strong sensitivity to subtle changes in trend, seasonality, and latent dynamics without relying on parametric assumptions, offering a flexible alternative to likelihood-based detectors but at a higher computational cost. Despite this overhead, SSA-based online detection is widely valued for its ability to capture complex temporal patterns and adapt to nonstationary environments in near real time.

3.2. **Alarm Detection.** In online change point detection using singular spectrum analysis (SSA), alarms are generated to differentiate between true and false change points by analyzing variations in the data over time. True change points are identified when the detection statistics, calculated from the trajectory matrix and normalized over historical data, consistently exceeds a predefined threshold H and aligns with significant shifts in the data pattern. False change points, on the other hand, may arise due to noise or minor fluctuations, often occurring when the window width N is too small. The flow chart of Figure 1 represents the detailed work flow of the proposed method, while the numerical example of next subsection explains the implementation of the method.

3.3. **Numerical Examples.**

Case 1: General Case: Using MATLAB, we analyzed $Y = \sin(2\pi t/\phi) +$ noise, with the parameters:

- $N = 34$, $M = 17$, $K = 18$, $p = 19$, $q = 20$, $H = 0.025$, $lengthY = 170$, $\phi = 15$

Initial matrices:

- Base matrix X_B^0: order 17×18
- Lag-covariance matrix R^0: order 17×17
- Eigenvector matrix U: order 17×17, with 17 eigenvalues

Detection results:

- Detection Statistic $\mathcal{D}_{n,I,p,q} = -5.3291 \times 10^{-15}$
- Normalized Statistic $\tilde{\mathcal{D}}_{n,I,p,q} = -3.1347 \times 10^{-16}$
- $\upsilon_n = -3.1347 \times 10^{-16}$, $S = 1$

Since $S = 1 > H = 0.025$, change points were detected at the following as shown in Figure 2:

55, 59, 61, 62, 63, 64, 65, 68, 70, 71, 75, 76, 77, 78, 81, 83, 84, 85, 86, 87, 89, 92, 95, 98, 99, 105, 106, 111, 112, 113, 115, 117, 118, 120, 123, 125, 126, 127, 128, 131, 133, 135, 137, 140, 143, 144, 145, 146, 147, 148, 149, 150, 153, 154, 156, 160, 161, 162, 163, 165, 166, 167, 168, 170, 171, 172.

Case 2: With Alarms: Analyzed $Y = \sin(2\pi t/\phi) +$ noise with parameters:

- $N = 36$, $M = 18$, $K = 19$, $p = 20$, $q = 21$, $H = 0.025$, $lengthY = 180$, $\phi = 15$

Initial matrices:

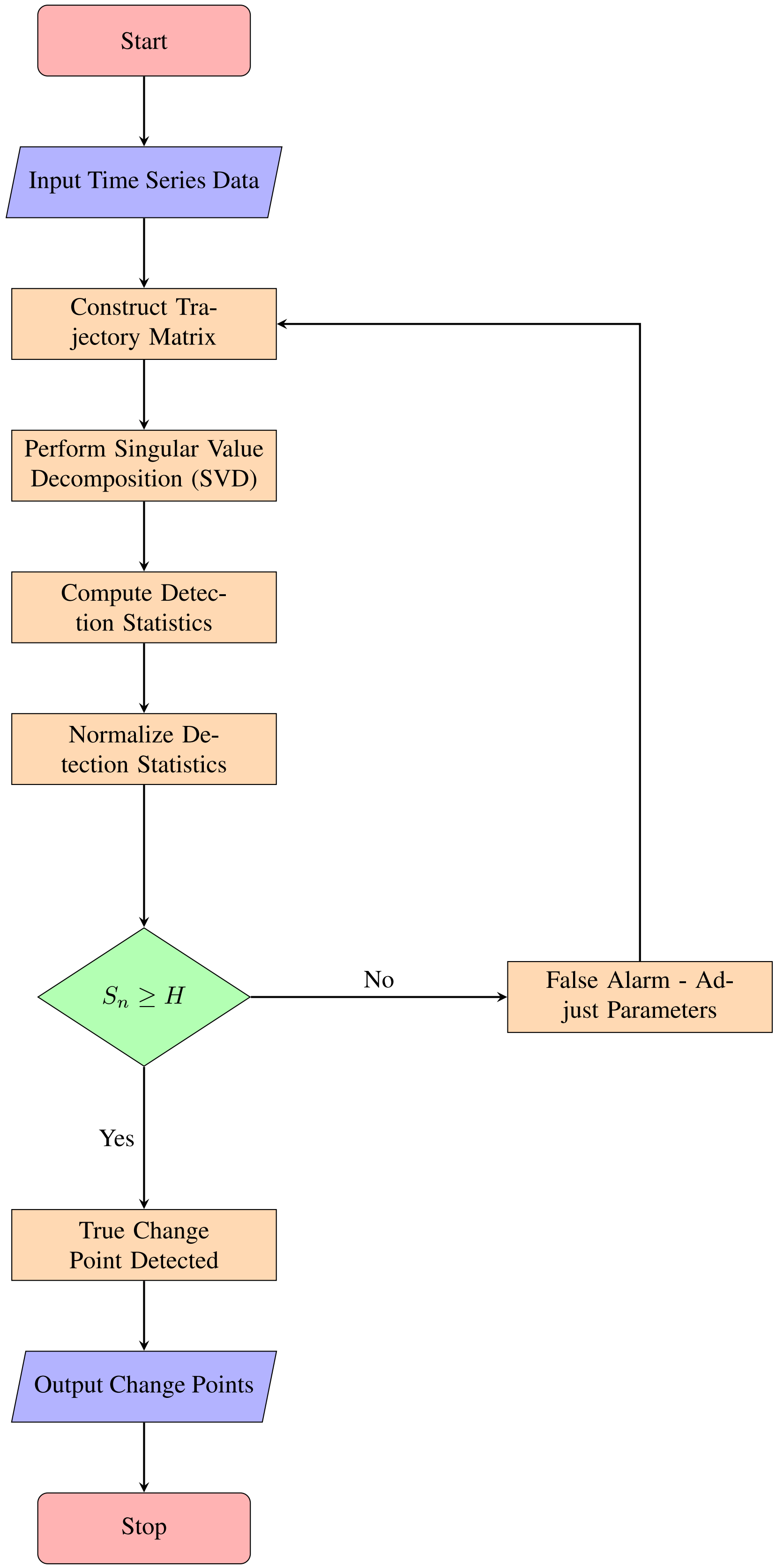

FIGURE 1. Work flow

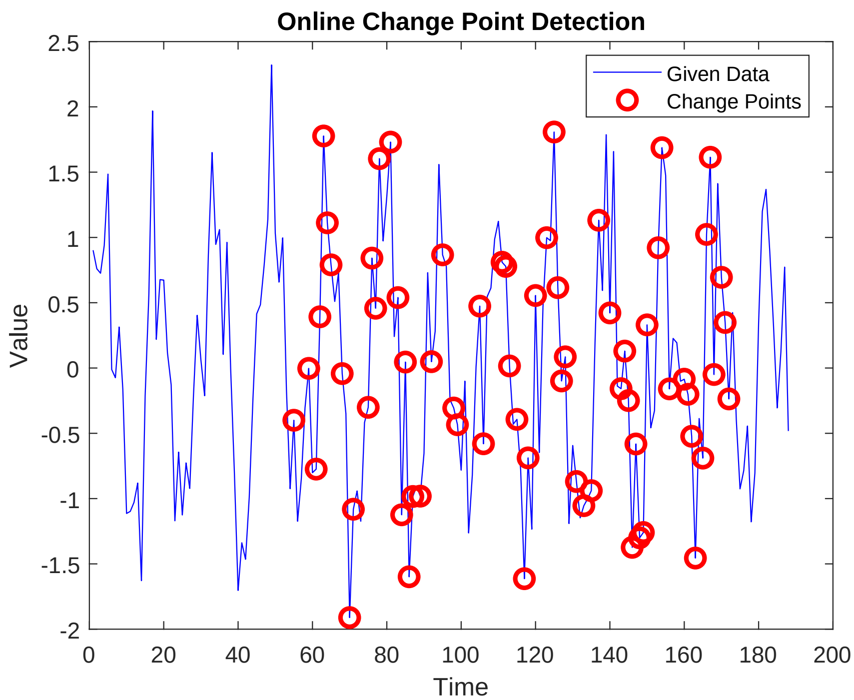

FIGURE 2. Online Change Point Detection Using SSA

- Base matrix X_B^0: order 18×19
- Lag-covariance matrix R^0: order 18×18
- Eigenvector matrix U: order 18×18, with 18 eigenvalues

Detection results:

- Detection Statistic $\mathcal{D}_{n,I,p,q} = -1.0658 \times 10^{-14}$
- Normalized Statistic $\tilde{\mathcal{D}}_{n,I,p,q} = -5.9212 \times 10^{-16}$
- $\upsilon_n = -9.8686 \times 10^{-16}$, $S = 0.6$

Since $S = 0.6 > H = 0.025$, change points were detected at the following as shown in Figure 3:

63, 65, 70, 71, 72, 73, 76, 77, 81, 83, 84, 85, 86, 87, 88, 89, 90, 93, 94, 96, 98, 99, 100, 102, 105, 108, 113, 114, 120, 121, 122, 125, 127, 129, 130, 132, 134, 135, 138, 143, 147, 148, 150, 151, 153, 157, 158, 159, 161, 163, 164, 165, 167, 171, 174, 177, 179, 180, 181, 182.

Alarm Count:

- True Alarms: 17 (63, 65, 70, . . . , 90)
- False Alarms: 43 (93, 94, 96, . . . , 182)

3.4. **Selection of Parameters.** A good selection of parameters will result in major changes in time series structure. Carefully adjusting the parameters could be necessary to detect

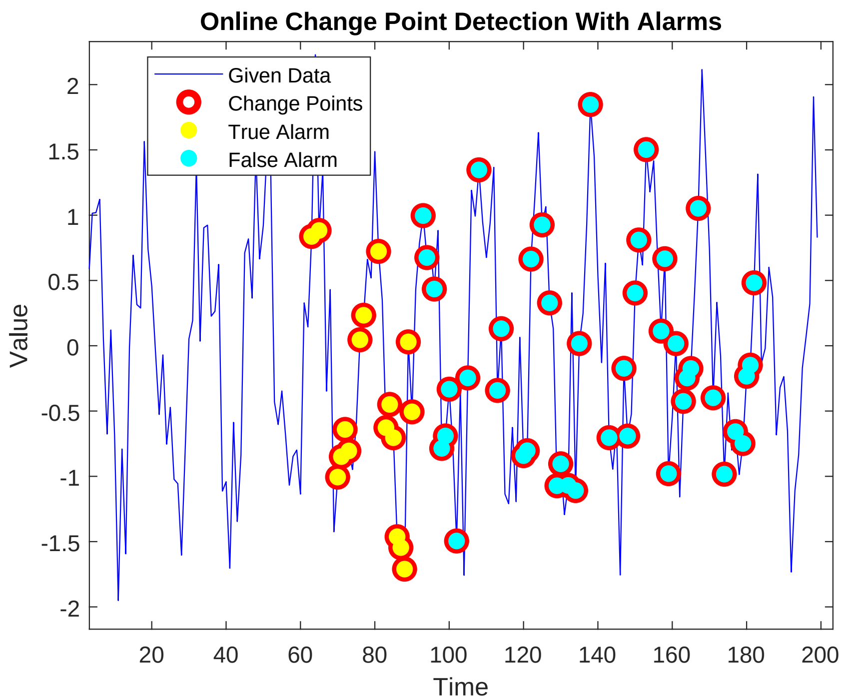

FIGURE 3. Online Change Point Detection Using SSA With True Alarm And False Alarm

minute variations in a noisy series. Some suggestions for this kind of adjustment are listed as:

N : The choice of window width N relies on the nature of structural changes we are looking for. If the time series is subject to tiny, gradual changes, then N shouldn't be too big because it may miss or smooth out changes. On the other hand, if N is too small, an outlier could be confused for structural change and thus false alarms could occur frequently. Hence, in general we choose N to be reasonably large.

M : Since the lag M depends on, so, when N is not very large, we choose $M = N/2$.

p and q : Test Statistics p and q depend on each other. At first p, should be less than q. Secondly, $p \geq K$, in general, where $K = N - M + 1$. In this case, the columns of the base and test matrices are different. On the other hand, when $p < K$, some of the columns of the base and test matrices overlap.
For q, it should be a bit greater than p, not too bigger.
And as $Q = p - q$. Often, it is very logical and even ideal to use $Q = q - p = 1$.

Data Size	30	300	1000	2000
Mean of given data	0.2282	0.0136	0.0145	0.0155
Processing Time	0.0025	0.1839	3.4026	48.4959
No. of Change points	2	31	225	297
Mean of Change points	1.0128	0.0562	-0.0938	0.0204

TABLE 1. Online Change Point Detection for $N = (datalength/3)$, $M = (N/2)$, $p = K + 1$, $q = p + 1$, $H = 0.25$

Data Size	20	200	1000	2000
Mean of given data	0.1661	-0.0070	0.0242	0.0148
Processing Time	0.0236	0.0589	1.5265	12.4116
No. of Change points	9	62	141	580
Mean of Change points	0.0323	0.1089	-0.0729	0.0182

TABLE 2. Online Change Point Detection for $N = (datalength/5)$, $M = (N/2)$, $p = K + 1$, $q = p + 1$, $H = 0.25$

4. EXPERIMENTAL RESULTS

Online Change Point Detection using Singular Spectrum Analysis (SSA) is an adaptive technique designed to identify changes in a time series as data continually arrives. In each iteration, we update our analysis using the latest data points, recalculating key statistics to detect any changes. Various experiments are performed in MATLAB with synthetic and real world data.
The synthetic data is generated by an almost periodic function of the form

$$x(t) = A\sin(2\pi f(t)) + B\cos(2\pi f(t)) + noise \tag{4. 1}$$

where $f(t) = t/l$ is the frequency of data and l is an arbitrary value, while A and B are amplitudes. The real world data analysis is performed by EMG signals obtained for Kaggle [8].
The parameters used in the computations include: the window width N, with M being half of N $(M = N/2)$; $K = N - M + 1$; and test samples p and q such that $0 \le p < q$.

4.1. **Online Change Point Detection.**

Here, we are using eq(4. 1) with A=1 and B=1, we obtain;

$$x(t) = \sin(2\pi t/l) + \cos(2\pi t/l) + noise$$

with $l = 15$.

4.1.1. *Case 1: Large Value of N.*

From Table-1 and Figure-4, we observed online change point detection using SSA for different data size ranging from 30 to 2000 with large value of N i.e., $N = (datalength/3)$. As, change point detection depends on the value of N, large value of N indicates that it skips the starting change points.

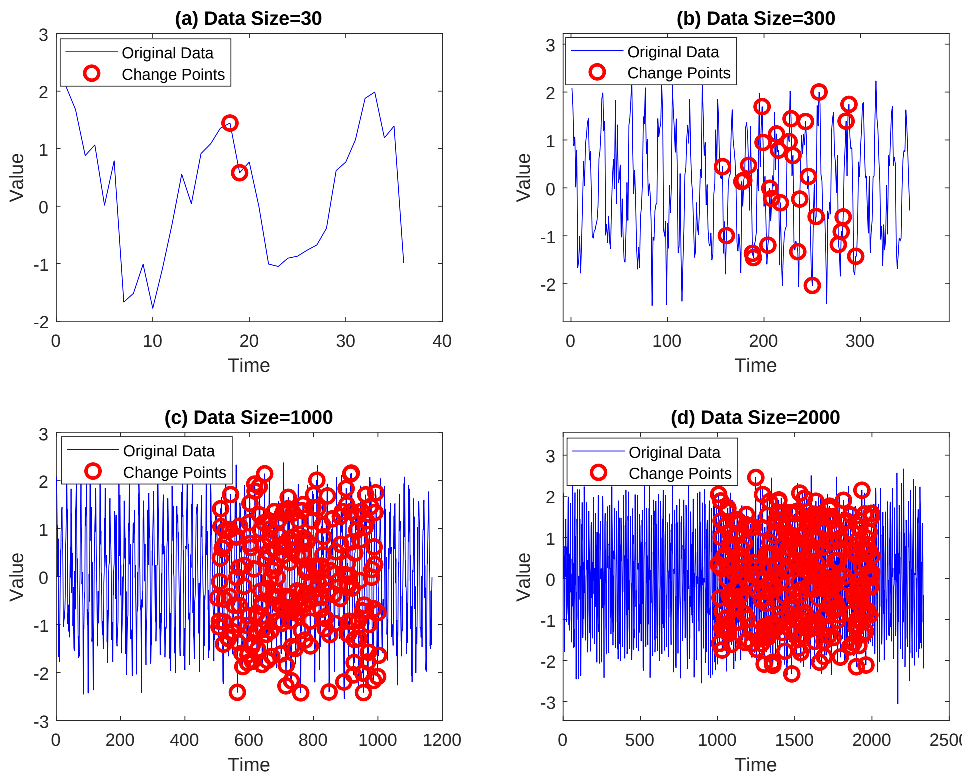

FIGURE 4. Online Change Point Detection Using SSA with Large value of N

Data Size	30	300	1000	2000
Mean of given data	0.2007	0.0174	0.0192	0.0144
Processing Time	0.0131	0.0443	0.9308	6.0003
No. of Change points	14	80	364	626
Mean of Change points	0.1269	-0.1230	0.0664	0.0112

TABLE 3. Online Change Point Detection for $N = (datalength/7)$, $M = (N/2)$, $p = K + 1$, $q = p + 1$, $H = 0.25$

4.1.2. *Case 2: Medium Value of N.* From Table-2 and Figure-5, we analyzed online change point detection using SSA for different data size starting from 20 to 2000 with medium value of N i.e., $N = (datalength/5)$. As, change point detection depends on the value of N, medium value of N indicates that it accurately detects the change points.

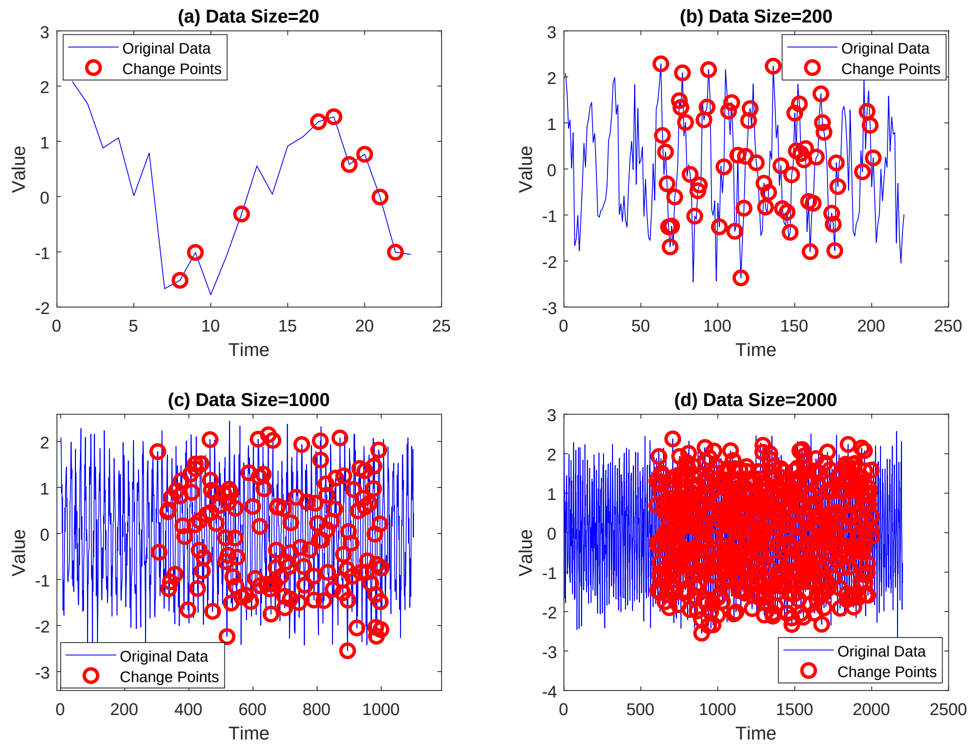

FIGURE 5. Online Change Point Detection Using SSA with Medium value of N

4.1.3. *Case 3: Small Value of N.* From Table-3 and Figure-6, we observed the detection of change points online using SSA for different data sizes starting from 30 to 2000 with a small value of N, i.e. $N = (datalength/7)$. As, change point detection depends on the value of N, small value of N indicates that it misunderstood outliers as structural change and as a result, False Alarms are raised. Additionally, this instance results in the development of Alarms to monitor changes that will be discussed in the next subsection.

4.2. **Online Change Point Detection With Alarms.**

4.2.1. *Synthetic Data.* : Consider eq(4. 1) with A=1 and B=1, we have;

$$x(t) = \sin(2\pi t/l) + \cos(2\pi t/l) + noise$$

with $l = 15$. Table-3 and Figure-6 reveal that for a too small value of N, the outliers are misunderstood as change points. So, in this case, we find which detected values of change points are true or false by generating false and true alarms depending on the length of time series. It can be observed from Table-4 and Figure-7 that true and false alarms have been

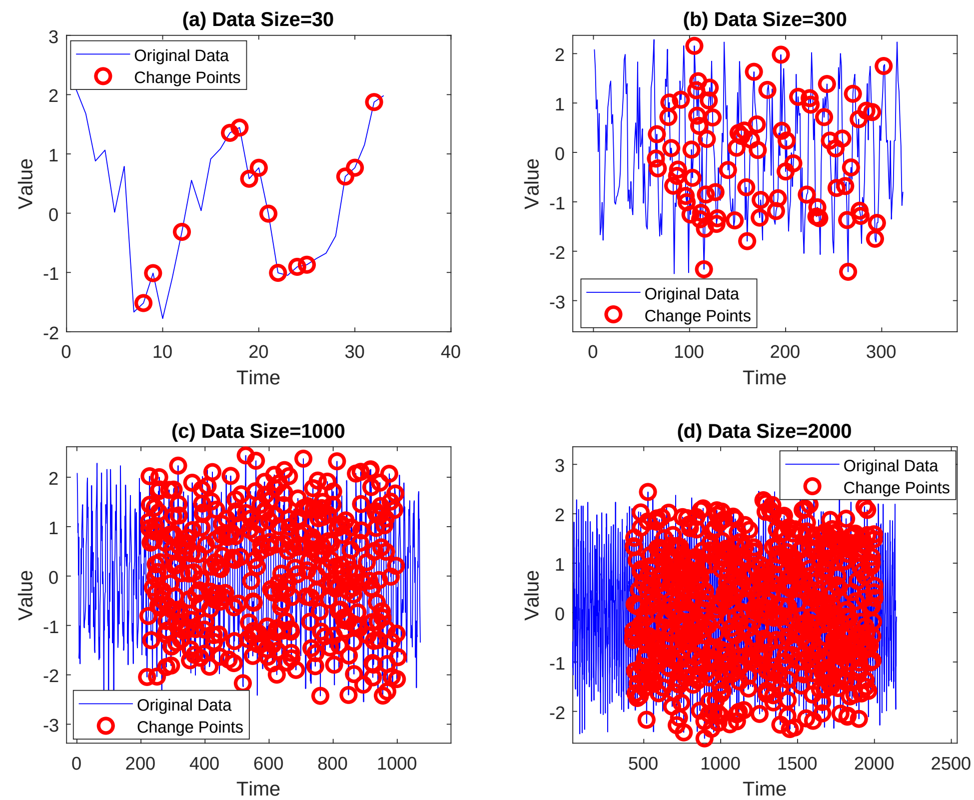

FIGURE 6. Online Change Point Detection Using SSA with Small value of N

detected for different data sizes ranging from 30 to 2000 with $N \approx (datalength/7), M = (N/2), p = K + 1, q = p + 1, H = 0.25$.

While the use of synthetic almost periodic signals provides a controlled environment for validating the algorithm's core mechanics and parameter sensitivity, it is acknowledged that real world data often presents more complex, non-stationary behaviors which are the ultimate test for any change point detection method.

4.2.2. *Real World Data.* : The real world data set, EMG [8] consists of eight electrodes with ten extracted features per electrode, resulting in 80 columns. The extracted features include standard deviation, root mean square, minimum, maximum, zero crossings, average amplitude change, amplitude first burst, mean absolute value, waveform length, and Willison amplitude. The datasets, labeled (a) to (j), range from 50 to 950, increasing by 100 in each step. Each dataset corresponds to a specific column of the extracted features. Detailed information and analysis results are provided in Table-5, Figure-8 and Figure-9.

Data Size	30	300	1000	2000
Mean of given data	0.2007	0.0174	0.0192	0.0144
Processing Time	0.0130	0.0455	0.9242	6.4506
No. of Change points	14	80	364	626
Mean of Change points	0.1269	-0.1230	0.0664	0.0112
No. of True Alarms	3	35	136	239
Mean of True Alarms	-0.9472	-0.1534	0.0534	-0.0494
No. of False Alarms	11	45	228	387
Mean of False Alarms	0.4199	-0.0993	0.0741	0.0486

TABLE 4. Online Change Point Detection For Synthetic Data With Alarms

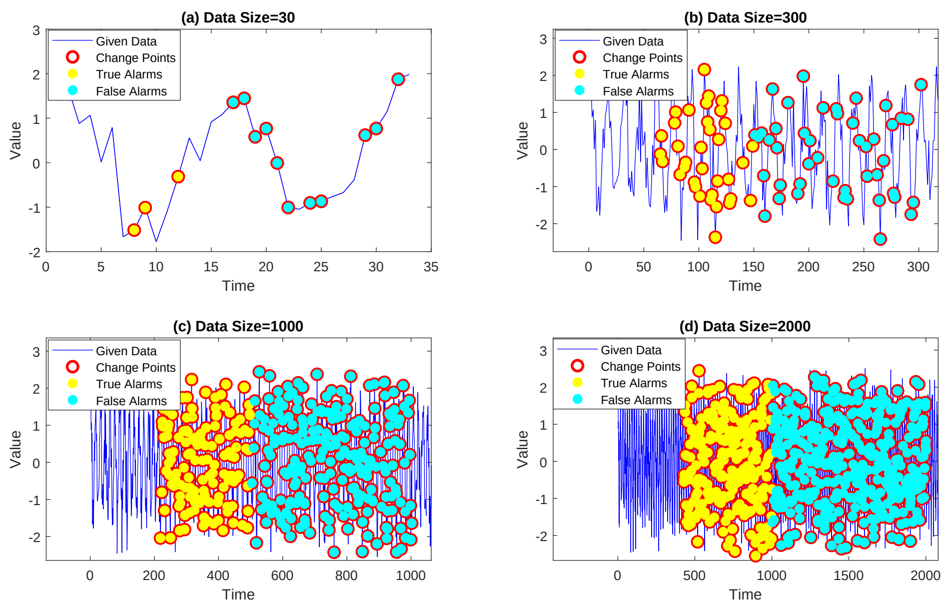

FIGURE 7. Online Change Point Detection For Synthetic Data With Alarms

Data Size	50	150	250	350	450	550	650	750	850	950
Mean of given data	0.0042	0.0190	-0.0784	0.0898	35.1704	0.0464	0.0309	0.0179	4.8981	4.2924
Processing Time	0.0265	0.0268	0.0350	0.0598	0.0992	0.2060	0.3141	0.4213	0.8517	0.8180
No. of Change points	13	58	81	112	153	166	191	245	270	319
Mean of Change points	0.0163	0.0314	-0.0776	0.0934	35.4583	0.0456	0.0297	0.0155	5.3295	4.8234
No. of True Alarms	6	22	29	35	52	55	75	87	105	100
Mean of True Alarms	-0.0048	0.0389	-0.0935	0.0669	31.7190	0.0346	0.0284	0.0044	4.1343	3.2153
No. of False Alarms	7	36	52	77	101	111	116	158	165	219
Mean of False Alarms	0.0344	0.0268	-0.0688	0.1055	37.3834	0.0511	0.0305	0.0216	6.0900	5.5577

TABLE 5. Online Change Point Detection For Real World Data With Alarms

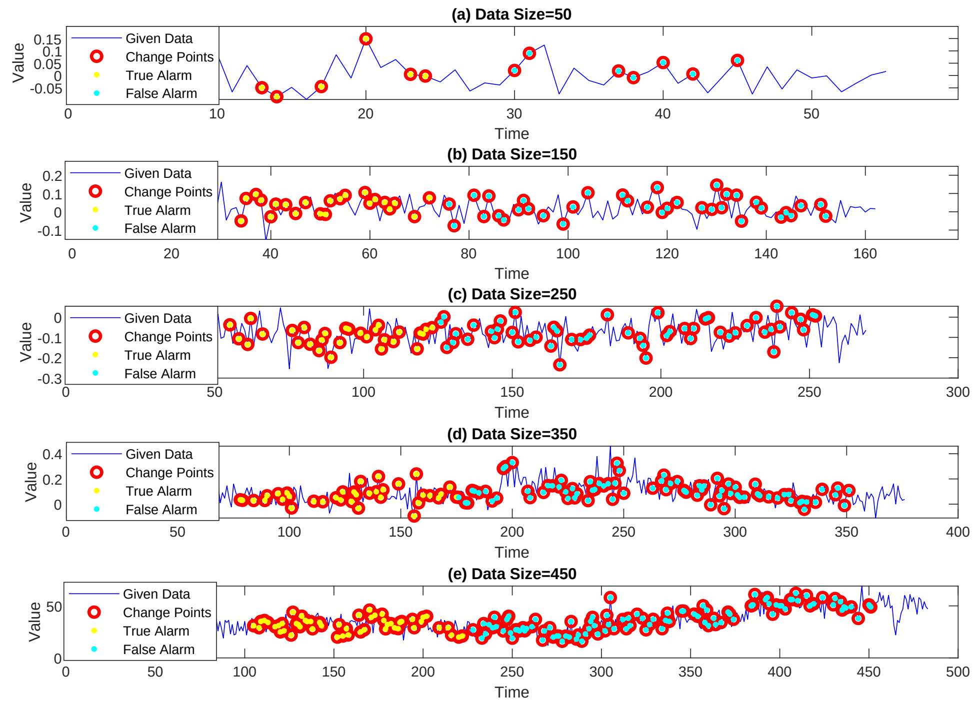

FIGURE 8. Online Change Point Detection For Real World Data With Alarms

The successful application of our algorithm to the multi-dimensional EMG dataset demonstrates its robustness beyond synthetic data. The method effectively identified change points across various feature streams (e.g., standard deviation, waveform length), which correspond to physiologically significant events in muscle activity. The consistent performance, evidenced by the clear separation of true and false alarms in Table 5, confirms the method's practical utility for complex, real-world bio signal analysis.

5. CONCLUSION

In this paper, the accuracy of online change point detection using singular spectrum analysis (SSA), has been tested utilizing both synthetic and real-world data. As, change point detection is solely dependent on the window width parameter N, it is important to comprehend how this parameter affects all other parameters, such as M, p, and q, and is itself dependent on the length of the time series. For synthetic data, almost periodic series of signals was used by varying N across different data sizes ranging from 30 to 2000. Three different cases for N were analyzed. It was observed that very large value of N missed some change points while for considerably small value of N , outliers were often mistaken

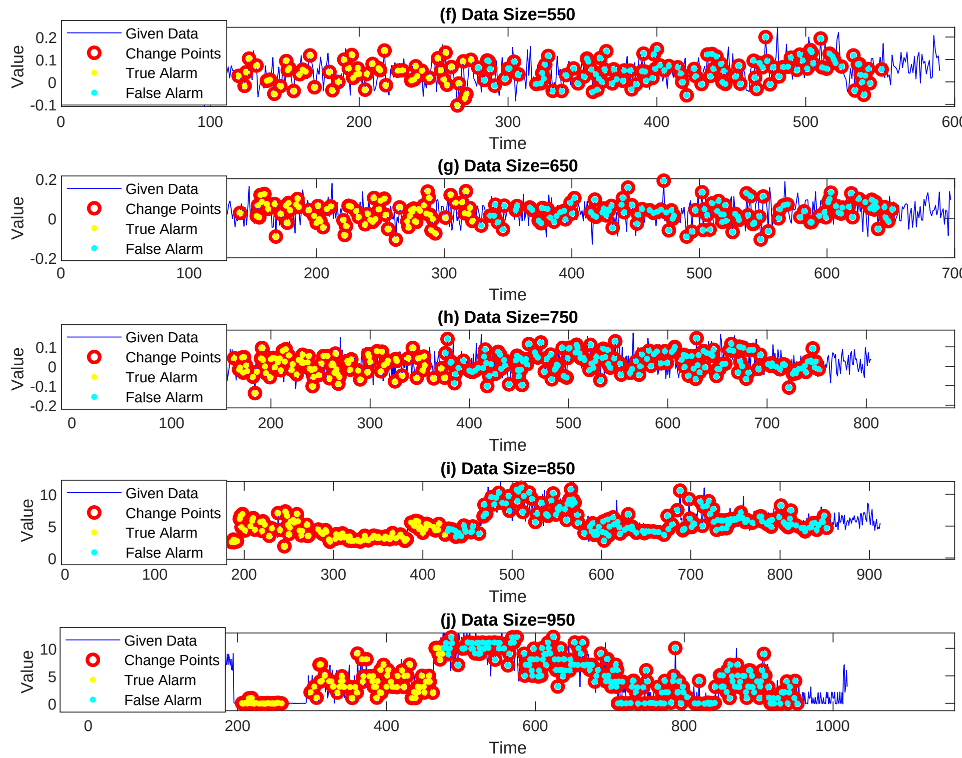

FIGURE 9. Online Change Point Detection For Real World Data With Alarms

for change points, resulting in false detections. Accurate change points were detected with medium or reasonably large value of N. To refine our detection process, particular case of very small value of N was considered, and experiments were made for both synthetic data (i.e., almost periodic series of signals), and real- world data (i.e., EMG-Dataset) and distinguished between true and false change points by developing a system of alarms based on the length of the data. Based on the experimental results, it was concluded that the best option for balancing the sensitivity and accuracy of change point detection is a medium or reasonably large value of N. This study emphasizes that choosing a suitable window width N for online data analysis is vital in order to accomplish reliable detection, limiting false alarms and guaranteeing accurate identification of significant changes.

Credit authorship contribution statement:

Saba Shakeel: Conceptualization, investigation, data analysis, programming, writing & editing. **Shazia Javed**: Methodology, validation, supervision, data curation and processing. **Uzma Bashir:** Formal analysis, investigation, review & editing.

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