Real-time incident detection: An approach for two interdependent time series

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Abstract- **A method is proposed to detect incidents that occur in two interdependent time series in real-time, estimating the incident time point from the profiles of the linear trend test statistics, computed on consecutive overlapping data window. The method is based on Slope Statistics Profile (SSP) utilizing adaptive data windowing, estimating real-time classifications of the linear trend profiles, according to two different linear trend scenarios, suitably adapted to the conditions of the problem. The method is applied on real datasets from a chemical process system that is situated at the premises of CERTH / CPERI, suggesting the occurrence of incidents, during experiments.**

Keywords-Time series; structural change; incident detection; linear trend.

I. INTRODUCTION

Structural change detection in time series is an important and difficult issue of increasing interest in many areas of meteorology and earth science [1,2], applied economics [3,4], communication and social networks [5-7] and urban data [8] among others. Some other terms for structural change that widely used in literature are anomaly detection or incident detection.

The term anomaly is defined as a pattern that does not conform to expected normal behavior, and it is a problem that not easily solved. Most of the existing anomaly detection techniques solve a specific formulation of the problem. In literature, one can find many approaches on anomaly detection, such as classification [7,9], clustering approach [10] and statistical approach [11].

The term *structural change* has several meanings in the time series literature, such as change of the slope of a linear trend, level shift (jump) and a combination of the slope change and level shift [12,13]. Statistical tests have been developed for detecting structural change in the trend function of a time series, often restricted to a single change, see among others [3, 14,15].

In transport systems exists the Automatic Incident Detection (AID), which is a very crucial technology. In literature, AID regarded as a classification problem. Thus, machine learning techniques, such as neural networks [16], support vector machines [17] and hybrid methods that use time series analysis and machine learning [18], are used to face this issue.

Existing statistical methods, approach the problem of incident detection on time series, taking into account only the time series of interest and employ statistical forecasting provide short-term forecasts. The main novelty of the proposed method is the real-time incident estimation (early detection) of two interdependent time series produced at the same time, by fusing their trends utilizing the Slope Statistics Profile methodology.

II. ADJUSTING TO A NEW PROBLEM

In order to address the problem of online incident detection on two interdependent time series, the method of Slope Statistic Profile (SSP) [15] is used and modified appropriately.

A. *Slope Statistic Profile (SSP) method*

The SSP method estimates the change point (or the breakpoint *T*) from the profile of a linear trend test statistic, computed on consecutive overlapping time windows along the time series. The selected test statistic for linear trend estimation it is showed that gives high power compared to other test statistics for both correlated and white noise residuals [19]. In SSP approach, a first candidate breakpoint T is the time point at which the profile crosses the threshold line of rejection of the null hypothesis of no trend at $\pm t_{w-2,1-a/2}$, where *a* is the significance level, *w* is the size of the sliding window and *t* follows the Student distribution with *w-2* degrees of freedom [20]. The search of T is confined in a time interval corresponding to the profile segment bounded by $t_{w-2,1-a_1/2}$ and $t_{w-2,1-a_2/2}$ for positive trends and by $-t_{t_{w-2,1-a_2/2}}$ and $-t_{w-2,1-a_1/2}$ for negative trends, where significance levels a_1 and a_2 for two side test are 0.20 and 0.05, respectively [15]. The selection of two significant levels is based on the assumption that there are not sudden and abrupt changes in natural variations, which means that some time is needed in order to pass from no trend to trend. Thus, the existence of two significant levels describes the transition between these situations. Hereafter, segment $(t_{w-2,1-a_1/2}, t_{w-2,1-a_2/2})$ will be denoted as upper segment and $t_{w-2,1-a_1/2}$, $t_{w-2,1-a_2/2}$ as UB_1 and UB_2, respectively and segment $(-t_{w-2,1-a_2/2}, -t_{w-2,1-a_1/2})$ will be denoted as lower segment and $-t_{w-2,1-a_1/2}$, $-t_{w-2,1-a_2/2}$ as LB_1 and LB_2, respectively. The computational study in [15] showed that sliding window should be long enough (larger than 30% of time series length), so that the estimation of other spurious onsets occurring at small time scales is avoided.

A very basic assumption in SSP method is that the time series is known. The online version of SSP presented in this article is an approach of SSP which has as main goal to give significant estimations of possible changes in linear trend of a time series, while the time runs.

The need for this different approach of SSP method came along, when the problem for online estimation of change of linear trend in two interdependent time series had arisen. Compared to SSP method, in the proposed approach, the estimation of time points of change is based in two interdependent time series. Also, the size of the sliding window is not fixed but resizes internally, according to fusion and real-time classification of profiles of the linear trend of both time series and an inner computation of precision, recall and F-measure (a brief description is given in section III).

B. Datasets

In order to evaluate the applicability of the SSP method a chemical process system that is situated at the premises of CERTH/CPERI is used as a pilot case. More specifically the behavior of a heating zone of a chemical reactor is studied. The objective is to be able to detect as soon as possible the occurrence of an abnormal event during the operation of the reactor. The temperature conditions of the reactor are maintained by a set of heating zones and are affected by the dynamically evolving exothermic reactions that occur. For each heating zone there is a measured input variable, the temperature, and an output variable, which is the percentage of operation of the heating resistance. In order to maintain the heating zone to a desired temperature set point, a controller is used that defines the percentage of operation of the heating resistance according to the measured temperature. A PID controller (proportional–integral–derivative) is used as a control loop feedback mechanism and continuously calculates an error value as the difference between the measured temperature and the desired setpoint. The controller attempts to minimize the error over time by adjustment of the control variable, which is the power supplied to the heating element.

These two interdependent signals constitute the tuple of the time series that will be fed to the SSP method. The output of the controller is directly applied to the heating element and is measured as a percentage of operation, at the range of 0 to 100% while the temperature is measured in degrees Celsius (^{0}C). The sampling time interval for the temperature is 3 seconds. Fig. 1 shows, two datasets (DS1 and DS2) that represent the controller output and the temperature during a 24hours period and are measured in minutes. These dataset will be used for the evaluation of the effectiveness of the SSP method. In both cases the controller output is modified in order for the temperature to be maintained at the desired set-point, for DS1 is 980^{0}C whereas at DS2 the set-point is 1180^{0}C. When the temperature increases above the set-point, the controller output is reduced and vise versa.

In case the temperature steadily decreases while the controller output increases then this indicates that a malfunction might be present that can be attributed to various reasons such as the short circuit of the heating resistance. The anomaly (or fault) that the SSP method will target to detect is the aforementioned case.

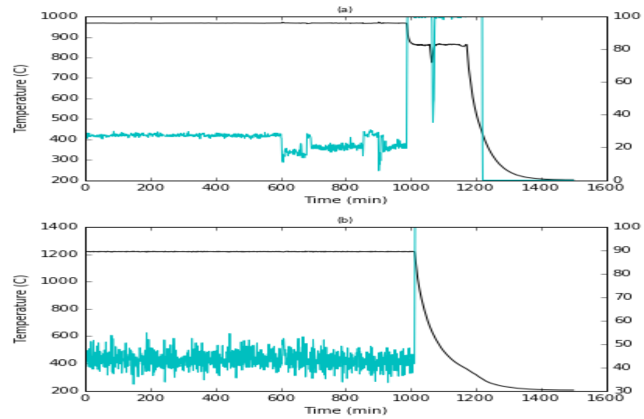

Fig. 1. Tested datasets (a) DS1 and (b) DS2.

The interdependency of signals is showed with the correlation diagrams (lag 1) between controller and temperature in Fig. 2, where both signals in both datasets are highly anticorrelated.

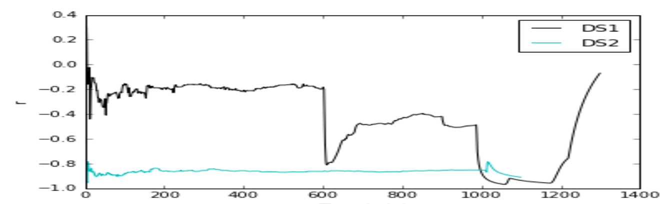

Fig. 2. Correlation diagrams of DS1 and DS2.

Therefore, the problem is to detect and estimate the time point(s) where temperature time series is falling and controller time series is rising, simultaneously. The incident is characterized mainly by the behavior of the controller output which reaches its maximum operating value (100%) and remains at this point while the temperature decreases. So far, the above procedure includes the element of human supervision, a fact that we intend to eliminate with the application of the proposed method.

III. THE METHOD OF REAL-TIME SLOPE STATISTIC PROFILE (RT-SSP)

The Real Time - Slope Statistic Profile method, denoted hereafter as RT-SSP, is based on the original idea of [18], where they first present SSP method for finding the onset and estimate the breakpoint T of linear trend in time series.

A. Linear trend test statistics and confusion matrices

In this section, we give a brief description of the linear trend test statistic that is used in SSP method together with the confusion matrices and evaluation metrics that will be used internally in the RT-SSP method. In the following, the parametric linear trend test for a sliding window of size w on the time series Y_t, $t = 1, \ldots, n$, is presented. Thus, for the first window $[Y_1, \ldots, Y_w]^T$ the least square estimator for the trend parameter β is obtained as

$$\hat{\beta} = \frac{\sum_{t-1}^{w}(t-\bar{t})Y_t}{\sum_{t-1}^{w}(t-\bar{t})^2} \tag{1}$$

where $\bar{t}$ is the average time. The standard error of $\hat{\beta}$ is estimated from the power spectrum

$$s(\hat{\beta}) = \left[2\int_0^{0.5} W(f)S(f)\right]^{1/2} \tag{2}$$

where $W(f) = \left|\sum_{t=1}^{w} b_t e^{-2\pi i f}\right|^2$ with $b_t = \frac{t-\bar{t}}{\sum_{t=1}^{w}(t-\bar{t})^2}$ and $S(f)$ denotes the sample power spectrum of ε_t given as $S(f) = \frac{1}{2\pi}(\hat{\gamma}_0 + 2\sum_{\kappa=1}^{w-1}\hat{\gamma}_\kappa \cos(2\pi f k)$. $\hat{\gamma}_\kappa$ denotes the estimate of the kth order autocovariance of ε_t, given as $\hat{\gamma}_\kappa = \frac{1}{w}\sum_{t=1}^{w-k}\hat{\varepsilon}_{t+k}\hat{\varepsilon}_t$ for $k > 0$, where $\hat{\varepsilon}_t = Y_t - \hat{a} - \hat{\beta}t$ are the estimated residuals ($\hat{a} = \overline{Y_t} - \hat{\beta}t$ and $\overline{Y_t}$ is the mean of the time series), and $\hat{\gamma}_0 = \frac{1}{w-2}\sum_{t=1}^{w}\hat{\varepsilon}_t{}^2$ for $k = 0$. The t-statistic for the parametric linear trend test is $t = \frac{\hat{\beta}}{s(\hat{\beta})} \sim t_{w-2}$.

The t-statistic is computed on overlapping data windows of size w with sliding step one. By this way, the profile of the t-statistic, denoted hereafter as RT-SSP curve ($\{RTSSP_i\}$ for $i = w, w+1, w+2, \ldots$) for the whole time series created so far, is obtained.

Real-time classification is a very essential part on the decision of sliding window size. Thus, $\{RTSSP_i\}$ are calculated for both time series and classified in real-time according to two different linear trend scenarios, suitably adjusted to the problem of estimation of abnormal temperature behavior incidents. Case 1 in Table I, presents the scenario where the controller output time series moves in the fields of no trend and negative trend and the expectation of temperature time series to move in the fields of no trend and positive trend, respectively. Case 2 in Table I, presents the exact opposite scenario with controller series to move in the fields on no trend and positive trend and the expectation of temperature time series to move in the fields of no trend and negative trend.

TABLE I. CONFUSION MATRICES FOR RT-SSP CURVES OF CONTROLLER AND TEMPERATURE TIME SERIES

Case 1 (Negative trend for controller series)		**Temperature RT-SSP**	
		$\boldsymbol{tstat} \in (\boldsymbol{LB_1}, \boldsymbol{UB_1})$	$\boldsymbol{tstat} \in (\boldsymbol{UB_1}, \boldsymbol{UB_2})$
Controlle r RT-SSP	$\boldsymbol{tstat} \in (\boldsymbol{LB_1}, \boldsymbol{UB_1})$	*TP*	*FP*
	$\boldsymbol{tstat} \in (\boldsymbol{LB_2}, \boldsymbol{LB_1})$	*FN*	*TN*

Case 2 (Positive trend for controller series)		**Temperature RT-SSP**	
		$\boldsymbol{tstat} \in (\boldsymbol{LB_1}, \boldsymbol{UB_1})$	$\boldsymbol{tstat} \in (\boldsymbol{LB_2}, \boldsymbol{LB_1})$
Controlle r RT-SSP	$\boldsymbol{tstat} \in (\boldsymbol{LB_1}, \boldsymbol{UB_1})$	*TP*	*FP*
	$\boldsymbol{tstat} \in (\boldsymbol{UB_1}, \boldsymbol{UB_2})$	*FN*	*TN*

The measures of precision, recall, accuracy and F-measure are calculated from the context of a confusion matrix, shown in Table I. True positive and false positive cases are denoted as TP and FP, respectively, while true negative and false negative cases are denoted as TN and FN. The instances of the confusion matrices shown in Table I are set in order to include both cases of positive and negative linear trend. Precision and recall cannot describe the efficiency of the method for selected parameters since good performance in one of those indices does not necessarily imply good performance on the other. For this reason, F-measure (or F_1-Score), a popular combination of precision and recall is commonly used as a single metric for performance evaluation. F-measure is defined as the harmonic mean of precision and recall.

B. The RT-SSP method

Based on the initial approach of SSP method, RT-SSP provides real-time estimations of possible changes in linear trend (or incidents), again every time RT-SSP curve crosses the threshold line of rejection of the null hypothesis of no trend at $\pm t_{w-2,1-a_1/2}$. Thus, each time point that RT-SSP curve is inside lower or upper segment this time point is denoted as an incident.

Testing of performance of RT-SSP method is divided in two parts. In the first part, the confusion matrix is calculated only when the computation of SSP method come to an end, for fixed sliding window sizes. Based on these simulations results, an initial estimate of the size of w comes off. In the second part, the sliding window is not fixed and it is resizes during the execution of the process, according to F-measures parameters, that are calculated internally and simultaneously with the execution of the process.

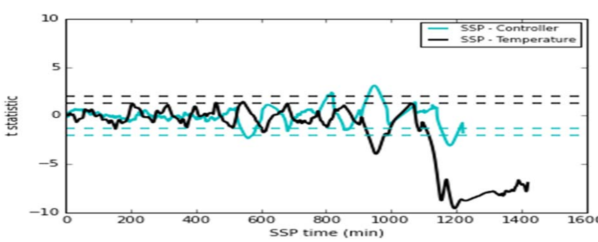

Fig. 3. Combined $\{RTSSP_i\}$, for controller and temperature for window size w = 80.

Fig. 3 shows the $\{RTSSP_i\}$ for both controller and temperature time series from DS1 dataset, for sliding window size $w = 80$. Also, the lowers and upper segments are shown in cyan and black, respectively. Because of the assumption that the form of controller time series reveals malfunctions on the temperature series, the ideal operation of RT-SSP method is that for every time point when the RT-SSP controller curve stays between lower and upper segment (null hypothesis of no trend is accepted), the RT-SSP temperature curve stays also between them at the exact time point. Also, for every time point when the RT-SSP controller curve crosses in lower (upper) segment, at the exact time point the RT-SSP temperature curve το cross in upper (lower) segment also. The case where RT-SSP controller curves crosses in lower segment is denoted as case 1, and the case where RT-SSP controller curves crosses in upper segment is denoted as case *2*. Because segment bounds are dependent from the size of w, as shown above, for $w = 80$ and $a = 0.05$ and 0.20, segment bounds are $\pm(1.29, 1.96)$. Table II shows the confusion matrices for both cases 1 and *2*, according to Fig. 3.

From the calculation of evaluation metrics, case *1* has precision 99.67%, recall 93.73%, accuracy 93.51% and F-measure 96.61% while case *2* has precision 89.97%, recall 96.35%, accuracy 87.70% and F-measure 93.05%. This result, leads as to conclude that the selection of a sliding window of size 80, will affect positively the estimation of possible incidents, because RT-SSP curves of both controller and temperature, follow opposite directions, as it would be the desired effect in sensitive areas.

TABLE II. CONFUSION MATRICES OF CONTROLLER AND TEMPERATURE $\{RTSSP_i\}$ (DS2), w = 80, FOR CASE 1 AND 2.

Case 1		**Temperature RT-SSP**	
		tstat $\in (-1.29, 1.29)$	***tstat*** $\in (1.29, 1.96)$
Controller RT-SSP	***tstat*** $\in (-1.29, 1.29)$	897	3
	tstat $\in (-1.96, -1.29)$	60	10

Case 2		**Temperature RT-SSP**	
		tstat $\in (-1.29, 1.29)$	***tstat*** $\in (-1.96, -1.29)$
Controller RT-SSP	***tstat*** $\in (-1.29, 1.29)$	897	100
	tstat $\in (1.29, 1.96)$	34	58

C. *Sliding window size selection*

Generally, the initial decision of the size of w is a very important part of the process, as it mentioned in introduction that the size w must be a percent of the size of time series. In real-time, there is no prior knowledge of the size of the time series and this fact makes this decision more difficult.

In order to decide for a proper size of sliding window, we simulate the sliding window parameter as follows: $w = (20{,}200{,}20)$.

Experimentally has been proven (through simulations) that the selection of proper size of w could be a tricky decision, a fact that is rather expected as the form of the time series of controller and temperature varies. This result, leads us to imply on RT-SSP method an adaptive sliding window, an approach that is not affected by the shape of the time series. The size of the adaptive sliding window will depend on the inner calculation of the confusion matrix (described above) and the computation of F-measure metrics for both cases 1 and 2. Initially, only the minimum and the maximum size of w have to be set. In our simulated cases the minimum and maximum size of w is set at 40 and 120 elements, respectively. Subsequently, in RT-SSP approach the size of w is re-calculated every 100 time points according to the real-time computed f-measure values for cases 1 and 2, hereafter denoted as FM_1 and FM_2. The size of w will be change by c time elements as follows: let assume the existence of a bound in F-measure value (FMB as percent). The existence of this bound aims to test the effectiveness of the proposed method in extreme conditions. Table III, explains the values of the adaptive window, based on calculated F-measures and FMB. The value FMB+3% consists of the bound where the sliding window increases.

TABLE III. VALUES AND INTERVALS FOR FM1 AND FM2 IN WHICH SLIDING WINDOW SIZE CHANGE (INCREASE OR DECREASE) OR REMAINS STEADY

Conditions	***Sliding window w***
$\boldsymbol{FM_1, FM_2 \in [FMB, FMB + 3\%)}$	*Steady*
$\boldsymbol{FM_1, FM_2 \geq FMB + 3\%}$	*Decrease by c*
$\boldsymbol{FM_1, FM_2 < FMB}$	*Increase by c*

Also, it should be mention that, as the calculation is performed online as the signals are modified through time, the increase of w is applied for the historical data of the time series.

IV. SIMULATION SETUP AND RESULTS

In the scheme that is tested here, the size of w that process starts varies in interval: SWS = (40,60,80) and the F-measure bound for FM_1 and FM_2 varies in interval: FMB = (0.90,0.91,0.92,0.93,0.94,0.95,0.96,0.97). The change of the sliding window varies in interval: SWC = (10,20,30), while the maximum size of w is fixed at 120 elements.

The testing will be applied to times series of datasets DS1 and DS2 as described at section II.B. Thus, the combination of all the values of SWS, FMB, SWC and tested series, gives a total of $3\ x\ 8\ x\ 3\ x\ 2 = 144$ cases.

Simulation results showed that in DS1 case the maximum size of w is reached for every case of FMB and SWS, which means that in a time series where several variations exist, an amount of past information is needed so as RT-SSP to extract significant results. However, for DS2 case the minimum size of w is used till FMB reaches 95%, while for FMB greater than 95%, the size of w is slightly increases. This major difference is explained from the fact that temperature series in DS2 case is steadier than in DS1, which means that for a steady time series as DS2, less information (or data) is needed in order RT-SSP to perform significantly. Experimentally has been shown that it is important to have a sliding window of variable size, because RT-SSP can be more flexible and more effective, depending on the form of the series encountered during the process.

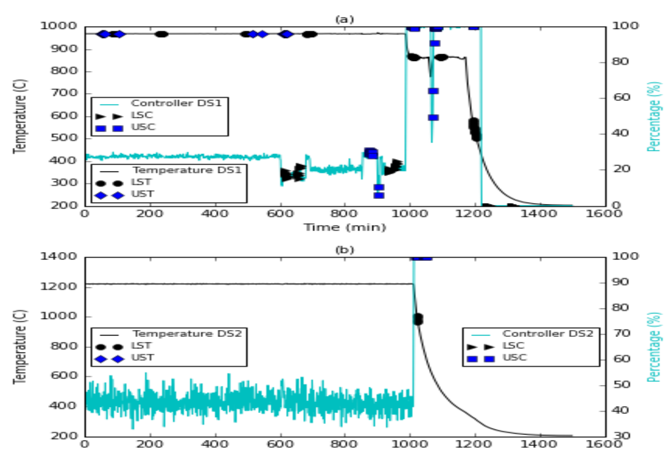

Fig. 4. Detected incidents for (a) DS1 and (b) DS2, from RT-SSP crossings in both upper and lower segments, where FMB = 95% and SWS = 40. LSC and USC markers denote the lower and the upper segment crossing, respectively, for controller time series. Same holds for LST and UST for temperature time series.

Fig. 4 shows the recommended incidents from the implementation of RT-SSP on all tested datasets, with F-measure set at 95% with starting *w* size at 40 elements. The incidents detection is the result of RT-SSP crossing in both upper and lower segments, for controller output and temperature time series. For DS1 (see Fig. 4a), RT-SSP detects a number of suggested incidents before the real incidents takes place. After the first real incident, the recommended incidents of RT-SSP for controller and temperature occur after some minutes. For DS2 (see Fig. 4b), the RT-SSP recommended incidents about the abnormal behavior of the temperature and the controller output concurrently denoted.

This approach of the problem of incident detection results too many false alerts during the process, in both controller and temperature time series. Thus, in order to avoid these false alerts, we impose a condition where only the time points where the RT-SSP of the controller and the temperature has passed simultaneously, contrary segments will be marked as incidents, hereafter.

The above condition is set only for detection of decrease in temperature. Fig. 5 shows the recommended incidents for DS1 based on this condition, where one can see that the number of estimated incidents have decreased significantly compare to prior approach (see Fig. 4).

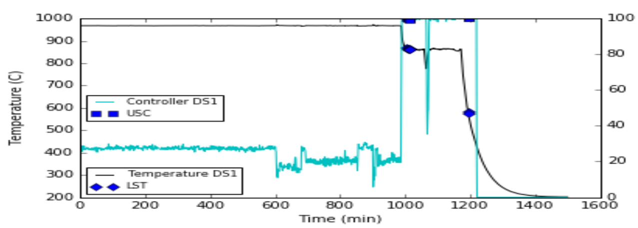

Fig. 5. Detected incidents for DS1, from RT-SSP common crosses in both upper and lower segments, where FMB = 95% and SWS = 40. USC and LST markers denote the upper segment crossing for controller and the lower segment crossings for temperature time series, respectively.

For DS2 case, the applied condition does not affect the estimated incidents, compared to the aforementioned results. The case where the SWS was set at 60 and 80 elements, do not show any significant changes on the estimation of incidents, since the RT-SSP method has the ability to decrease the *w* as the time series, and consequently the RT-SSP curves of controller and temperature do not show any abnormalities.

V. CONCLUSIONS

The proposed method of RT-SSP was developed for the detection of abnormal temperature-controller output behavior incidents of a heating zone at a chemical reactor of a pilot plant at CERTH/CPERI. In order to achieve acceptable performance, the RT-SSP method uses an adaptive sliding window applied to the interdependent time series (temperature and controller output). The proposed method applies real-time classification, based on two linear trend scenarios of the controller time series in order to evaluate the real-time information and to properly adjust the size of the adaptive sliding window. Overall the RT-SSP method, for FMB=95% and SWS=40, manages to detect and estimate the time points of temperature dropping very close, in minutes, to the real ones.

ACKNOWLEDGEMENT

This work has been partially supported by the European Commission through the project HORIZON 2020-INNOVATION ACTIONS (IA)-636302-SATISFACTORY.

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