DISTRIBUTED ROBUST CHANGE POINT DETECTION FOR AUTOREGRESSIVE PROCESSES WITH AN APPLICATION TO DISTRIBUTED VOICE ACTIVITY DETECTION

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ABSTRACT

The detection of abrupt changes in signals that are observed by wireless sensor networks (WSN), is an important research area with potential applications, e.g., in fault detection, prediction of natural catastrophic events, and speech segmentation. We consider the distributed robust detection of changes in the parameters of autoregressive (AR) models. Our method is robust on a single sensor level by suppressing the effect of outliers and impulsive noise via a robustified distance metric between a long-term and a short-term AR model. The new distributed change detector works without a fusion center and incorporates a weighting based on signal-to-noise-ratio (SNR) information, to ensure that every node will, at least, maintain its single node performance. A Monte-Carlo simulation study is provided which compares the proposed detector to a centralized version, in terms achievable detection rates and mean detection delay. Furthermore, an application example of distributed voice activity detection for a noisy speech signal is given.

***Index Terms*—** Change Point, Distributed Detection, Robust, Voice Activity, Autoregressive Process

1. INTRODUCTION

The detection of abrupt changes has received considerable attention and has been successfully applied to areas as diverse as, fault detection and monitoring, quality control, prediction of natural catastrophic events, and speech segmentation [1, 2, 3, 4]. E.g., in industrial monitoring, the early detection of changes in the operating conditions of a machine allows for interventions that enhance safety and reduce costs. In the last few years, the increased availability of small low-cost sensors that are equipped with a battery, or secondary power supply, a processing unit and a radio for wireless communication has created the demand for detecting changes by use of wireless-sensor-networks (WSN) [5, 6]. Only recently, fully distributed change detection methods, which do not require a fusion center (FC) but rely on local neighborhood communication between sensors of an *ad-hoc* WSN were proposed [6]. These methods are less sensitive to a single node failure and are scalable to larger network sizes, since the bottleneck transmission to a single point is avoided [7, 8]. A key difficulty in the detection of changes is that these must be extracted from available measurements that contain a mix of information, which is only partly related to changes, and also contains perturbations, such as stationary or non-stationary impulsive noise and outliers. Robust signal processing methods [9], are able to provide increased reliability in case of impulsive noise and outliers while maintaining near optimality under nominal conditions. Distributed robust change detection has not been considered, up to now.

Contributions: We researched the detection of abrupt changes in signals that are observed by a WSN, and developed an algorithm to robustly detect changes in the parameters of AR models. Speech and seismic signals are potential applications [2, 3]. Different SNR and outlier contaminations at each sensor were taken into account in the design of the algorithm. On the one hand, our proposed algorithm is designed to be robust against outliers and impulsive noise on a single node level by robustifying [3] which detects non-additive changes in AR models. On the other hand, we introduce a cooperative distributed scheme, through which nodes with a low SNR or many outliers can achieve a performance which they would not be able to, without cooperation, while high SNR nodes do not experience a performance degradation, due to a proposed weighting scheme. A Monte-Carlo simulation study is provided which compares the proposed detector to a centralized approach which requires a FC, in terms of detection rates and mean detection delay for different noise and outlier scenarios. Furthermore a distributed voice activity detection example for a noisy speech signal is provided.

Organization: Section 2 briefly revisits single sensor change detection for an AR process, while Section 3 presents the proposed distributed change detector. Section 4, provides a Monte-Carlo simulation study that compares the proposed method to a centralized version which uses a FC. This section also provides a voice activity detection application for a noisy

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speech signal. Section 5 concludes the paper.

2. SINGLE SENSOR CHANGE DETECTION FOR AN AUTOREGRESSIVE PROCESS

Assume an AR process

$$X_n + \sum_{p=1}^{P} a_p X_{n-p} = Z_n, \tag{1}$$

where P is the model order, Z_n is zero-mean independent and identically distributed (i.i.d.) Gaussian process with variance $\sigma^2 < \infty$, a_p, $p = 1, \ldots, P$ are the AR-parameters, and the roots of $A(z) = 1 + a_1 z^{-1} + \ldots + a_P z^{-p}$ lie inside the unit circle. Let a signal of length N be described by the AR-parameter vector $\mathbf{a}^0$ for $n < n_{cp}$, where n_{cp} is the unknown change point, while for $n \geq n_{cp}$ the parameters abruptly change to $\mathbf{a}^1$.

A fundamental change detection approach is the cumulative sum (CUSUM) algorithm which compares the integration of the signals to a threshold [3]. To detect changes in an AR process, the so-called divergence-algorithm [1, 2] compares two AR models based on a long-term (LT) and a short-term (ST) observation window.The LT-model uses a growing memory while the ST-model is based on a sliding window of fixed size L. The distance metric is the cross-entropy between the conditional distributions of these two models, which assuming (1) yields

$$\begin{aligned} s_n =& \frac{1}{2}\left(2\frac{\hat{z}_{n,LT}\hat{z}_{n,ST}}{\hat{\sigma}^2_{ST}} - \left[1 + \frac{\hat{\sigma}^2_{LT}}{\hat{\sigma}^2_{ST}}\right]\right. \\ & \left. \times \frac{(\hat{z}_{n,LT})^2}{\hat{\sigma}^2_{LT}} + \left[1 - \frac{\hat{\sigma}^2_{LT}}{\hat{\sigma}^2_{ST}}\right]\right), \end{aligned} \tag{2}$$

where $\hat{z}_{n,LT/ST} = x_n - \sum_{p=1}^{P} \hat{a}_{p,LT/ST} x_{n-p}$ are the LT- and ST-innovations estimates with standard deviations estimates $\hat{\sigma}_{LT}$ and $\hat{\sigma}_{ST}$, respectively. The CUSUM is defined by

$$S_n = S_{n-1} + s_n + \delta, \tag{3}$$

where δ is a constant factor assigned a priori to ensure positive drift of the CUSUM before and a negative drift after the change point [3, 2]. The Hinkley-rule [10]

$$\max_{r: L < r \leq n} S_r - S_n > \lambda, \tag{4}$$

where λ is the detection-threshold, localizes a change in the drift, and a change point (CP) is the value r maximizing (4).

3. DISTRIBUTED ROBUST CHANGE POINT DETECTION FOR AN AUTOREGRESSIVE PROCESS

Consider a distributed network consisting of K nodes. A set of nodes connected to node k (including k) is called its neighborhood $\mathcal{N}_k$, and the number of nodes connected to k is the degree d_k. All parameters referring to node k are indicated with the superscript (k).

3.1. Single sensor robust change detection

In the first step of our approach, each node locally tests for changes. In the presence of impulsive noise or additive outliers (AO), the change detector based on (2) breaks down. We thus propose:

$$\begin{aligned} s_n^{(k)} =& \frac{1}{2}\left(2\frac{\psi(\hat{z}^{(k)}_{n,LT})\psi(\hat{z}^{(k)}_{n,ST})}{(\hat{\sigma}^{(k)}_{ST})^2} - \left[1 + \frac{(\hat{\sigma}^{(k)}_{LT})^2}{(\hat{\sigma}^{(k)}_{ST})^2}\right]\right. \\ & \left. \times \frac{(\psi(\hat{z}^{(k)}_{n,LT}))^2}{(\hat{\sigma}^{(k)}_{LT})^2} + \left[1 - \frac{(\hat{\sigma}^{(k)}_{LT})^2}{(\hat{\sigma}^{(k)}_{ST})^2}\right]\right) \end{aligned} \tag{5}$$

In (5), we estimate the AR parameters with the robust and computationally efficient median-of-ratios estimator (MRE) [11, 9], which uses robust autocorrelation function estimates based on sample medians. Innovations standard deviations estimates are robustly estimated with the normalized median-absolute-deviations scale estimator [12, 9]. Outliers in $\hat{z}^{(k)}_{n,LT/ST}$ are suppressed, e.g. by applying Tukey's $\psi(x)$-function

$$\psi(x) = \begin{cases} x - 2\frac{x^3}{u^2_{Tuk}} + \frac{x^5}{u^4_{Tuk}} & |x| \leq u_{Tuk} \\ 0, & |x| > u_{Tuk} \end{cases}. \tag{6}$$

3.2. Distributed robust change detection

Change detection with sensor networks can be highly useful, for example in distributed speech processing and seismic monitoring. While robustness at a single sensor level is crucial to success of any robust change detector, there exist scenarios that cannot be resolved without cooperation. We distinguish four cases:

- Case 1: $\mathbf{y}^{(k)} = \mathbf{x}^{(k)}$.
- Case 2: $\mathbf{y}^{(k)} = \mathbf{x}^{(k)} + \Phi^{(k)}$, with $\Phi^{(k)}$ being a sparse vector with large values.
- Case 3: $\mathbf{y}^{(k)} = \mathbf{x}^{(k)} + \mathbf{v}^{(k)}$, with $\mathbf{v}$ being additive white Gaussian noise (AWGN).
- Case 4: $\mathbf{y}^{(k)} = \mathbf{x}^{(k)} + \mathbf{v}^{(k)} + \Phi^{(k)}$.

The boldface-letters represent $1 \times N$ row-vectors. Distributed robust change detection enables nodes to detect change points, even if, e.g., in Case 2, the number of non-zero entries of $\Phi^{(k)}$ exceeds the breakdown point [9] of the robust estimator, or if the sensor operates in a low SNR regime (Case 3).

We next describe our proposed distributed method: Let each node take a measurement and compute $s_n^{(k)}$ based on (5). Next, $S_n^{(k)}$ is computed in a distributed fashion:

$$S_n^{(k)} = \sum_{l \in \mathcal{N}_k} c^{(l,k)} S^{(k)}_{n-1} + \sum_{l \in \mathcal{N}_k} c^{(l,k)} s_n^{(k)} + \delta, \tag{7}$$

where $c^{(l,k)}$ are real, non-negative entries of the $K \times K$ weighting matrix C such that $c^{(l,k)} = 0 \quad \text{if} \quad l \notin \mathcal{N}_k$. The $c^{(l,k)}$ define how data is weighted within a neighborhood. One could use uniform weights $c^{(l,k)} = \frac{1}{d_k}$ for all $l \in \mathcal{N}_k$. If SNR information is available, e.g., via parametric estimation of the

Nodes	1	2	3	4	5	6	7
SNR	-6dB	-6dB	-6dB	0dB	10dB	10dB	6dB
AO	0.01	0.1	0.1	0.1	0.02	0.01	0

Table 1. SNR of the AWGN and fraction of the samples that is contaminated with additive outliers for each of the nodes of the WSN that is depicted in Fig. 2.

AWGN variance $\hat{\sigma}_v^{(k)}$, we propose to additionally constraint $c^{(l,k)} = 0$ for all $l \in \mathcal{N}_k$ which have $\mathrm{SNR}^{(l)} < \mathrm{SNR}^{(k)}$ and $c^{(l,k)} \sim \mathrm{SNR}^{(l)}$, otherwise. The proposed change detector is summarized below:

Step 1: Initialization of $\hat{\mathbf{a}}^{(k)}_{L,LT/ST}$, $\hat{\sigma}^{(k)}_{L,LT/ST}$, and $\hat{\sigma}_v^{(k)}$;
Exchange $\hat{\sigma}^{(k)}_{L,LT/ST}$ and $\hat{\sigma}_v^{(k)}$;
Set weights $c^{(l,k)}$ for $l \in \mathcal{N}_k$;

Step 2: For each $n > L$:
Compute robust local estimates $\hat{\mathbf{a}}^{(k)}_{n,LT/ST}$, $\hat{\sigma}^{(k)}_{n,LT/ST}$ and $\hat{z}^{(k)}_{n,LT/ST}$;
Weight residuals using (6) with $u_{Tuk} = u\hat{\sigma}^{(k)}_{n,LT/ST}$;
Compute robust local CUSUM $s_n^{(k)}$ by (5);
Exchange $S_{n-1}^{(k)}$ and $s_n^{(k)}$ with $\mathcal{N}_k$;
Compute $S_n^{(k)}$ by (7);
If $\max\limits_{r:L<r\leq n} S_r^{(k)} - S_n^{(k)} > \lambda$
Set estimated change point equal r;
Set $n = 0$ and re-initialize algorithm;

4. NUMERICAL EXPERIMENTS AND REAL WORLD APPLICATION

In this section, we investigate the performance of the proposed algorithm using simulated and real data. For all examples $L = 200$, $\lambda = 70$, $\delta = 1.5$, $\sigma_z = 1$, and $u_{Tuk} = 2.5\sigma_x$. The AO were generated from a zero-mean Gaussian distribution with variance $5\sigma_z^2$. In all cases, the change of an AR(3) process from parameters $\mathbf{a}^0 = [1, 0.95, 0.25, 0.06]$ to $\mathbf{a}^1 = [1, 0.3, 0.35, 0.04]$, is considered.

4.1. Single sensor robust change detection for an AR(3)

We first illustrate the single sensor robustness of our algorithm. The top graph in Fig. 1 shows a clean signal realization (Case 1) of $N = 2000$ samples. The bottom graph shows the same signal, but now contaminated with 1 % AO (Case 2). The solid black line indicates the CP at $n_{cp} = 1001$. The dash-dotted line shows the estimates by [3], while the green dashed line represents our algorithm that uses (5). points.

4.2. Distributed and robust change detection for an AR(3)

We next consider a WSN of $K = 7$ nodes, as depicted in Fig.2. We assume that the same signal is measured without delay at all nodes and that all nodes have perfect connectivity. However, each sensor has to deal with a different amount of

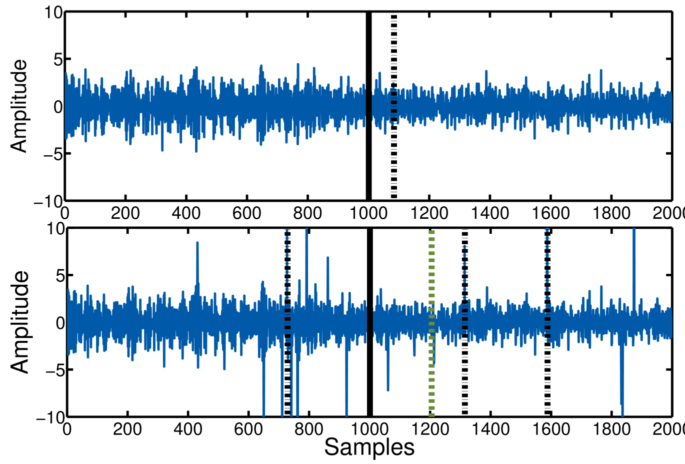

Fig. 1. Single sensor robustness for AR(3) with CP, as indicated by the solid black line. (top) clean data. (bottom) 1 % additive outlier. Black dash-dotted line indicates estimated CP with divergence CUSUM detector [3], while green dashed line indicates proposed robust change detector.

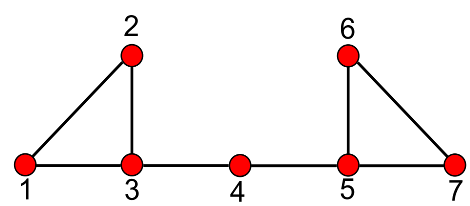

Fig. 2. Wireless sensor network configuration.

AO and AWGN of different variances (Case 4), see Table 1. In Fig. 3, the change detection result is shown exemplary for nodes 3 (top) and 5 (bottom).

4.3. Monte-Carlo simulation study

Based on the WSN displayed in Fig. 2 and the parameter-settings above, we present network-wide mean results that are averaged over 200 Monte-Carlo experiments. Performance is measured by the true-positive-rate (TRP) and the false-positive-rate (FPR) as in [4]. We define N_{TA} as the total number of alarms and N_{CD} as the total number of correct detections over all thresholds. N_{cp} is the number of actual change points per threshold, which is in our case $N_{cp} = 200$. TPR is defined as $\frac{N_{CD}}{N_{cp}}$ and FPR as $\frac{N_{TA}-N_{CD}}{N_{cp}}$. In Fig. 4, we plot the network wide mean-delay over the specified range of thresholds. In Fig. 5 we present the mean TPR and FPR.

4.4. Real data example: voice activity detection for a noisy speech signal

We now show how the proposed algorithm is used for the segmentation of a speech signal into active speech and non-speech parts. $K = 3$ nodes that could be, e.g., mobile-phones, that cooperate in an ad-hoc network, measure a speech signal. The speech is affected by AWGN and all the nodes are

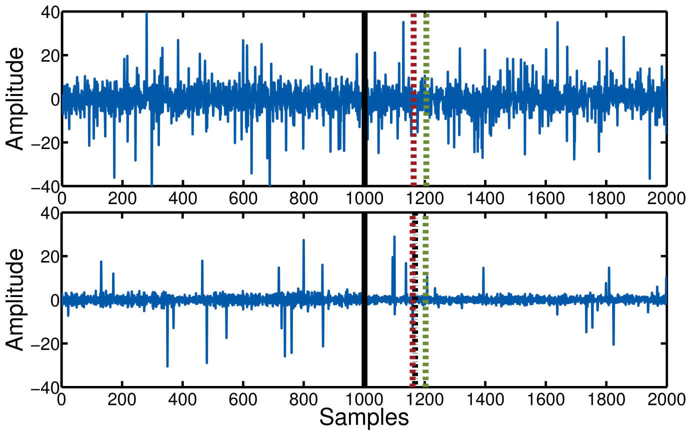

Fig. 3. AR(3) with CP, as indicated by the solid black line. (top) Node 3 with SNR=-6dB and 10 % AO. (bottom) Node 5 with SNR=10dB and 2 % AO. The dash-dotted black line shows estimated CP without cooperation. The green dashed line depicts results of the proposed distributed detector for uniform weights, while the red dashed line incorporates the proposed SNR-based weighting.

additionally disturbed by impulsive noise (10 % AO). Note that, in this setting, each sensor receives a delayed and filtered version of the signals based on a room-impulse-response with a reverberation time of $T_{60} = 0.5$ seconds. The signals consist of 35,000 samples using a sampling-frequency of 16 kHz. We set $\lambda = 100$, $\delta = 1.2$. For $c_{k,l}$ we again used uniform weights. Solutions for one node are depicted in Fig. 6. Changes are marked by hand and indicated by solid black-lines. Estimated changes are indicated with green dashed lines. In the top graph, results for a single node without cooperation are shown. Changes are correctly detected, however, the algorithm leads to 4 false-alarms which results in $FPR = 0.4$. In the bottom graph, the nodes cooperate, as proposed in our algorithm which yields $FPR = 0.2$.

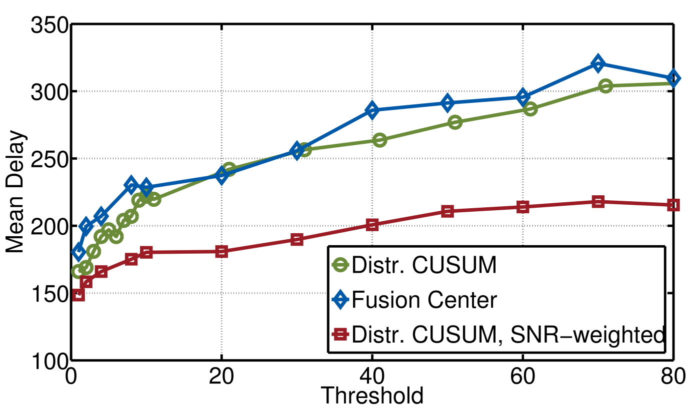

Fig. 4. Network-wide mean change detection delay, averaged over 200 Monte-Carlo experiments.

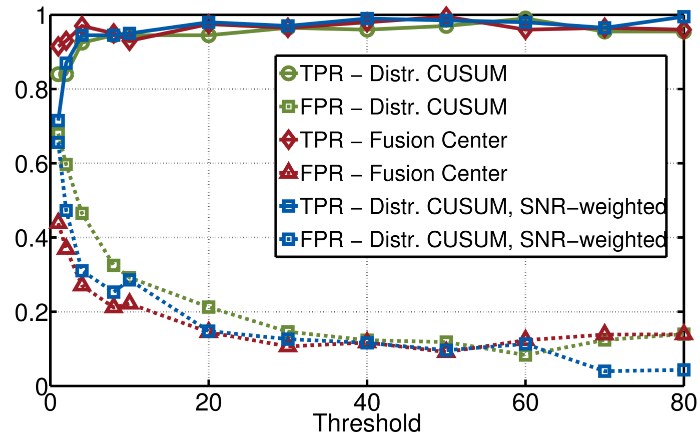

Fig. 5. Network-wide mean true-positive-rate (TRP) and false-positive-rate (FPR), averaged over 200 Monte-Carlo experiments.

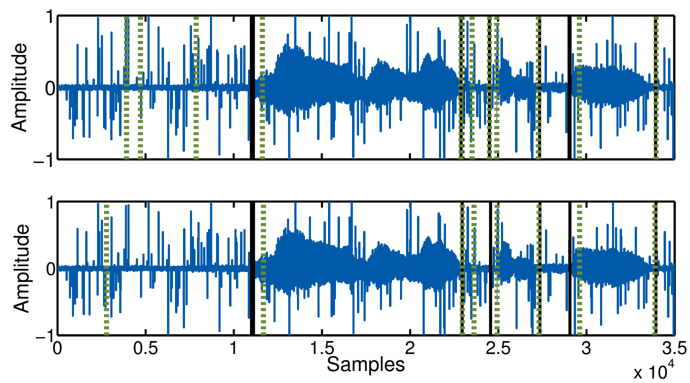

Fig. 6. Noisy speech signal observed by a WSN. (top) Result of robust change detection at a single node without cooperation. (bottom) proposed robust and distributed change detection at the same node.

5. CONCLUSION

Our work addressed the problem of detecting abrupt changes of signals that are observed by a WSN. We considered the case of non-additive changes autoregressive models and transformed the divergence CUSUM algorithm to a distributed and robust framework. Simulations showed that the performance can be increased in realistic situations, e.g., when some sensors operate in a low SNR regime, or are contaminated severely by outliers. We also showed how the proposed algorithm may be useful for segmentation of speech-signals that are measured by a sensor network. The preliminary results indicate that the proposed algorithm may be useful in voice activity detection for distributed speech enhancement. Future work inclusdes seeking adaptive cooperative rules for the selection of δ and λ and exploring further change point detection algorithms.

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