A trend filtering approach for change point detection in MOX gas sensors

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ABSTRACT

Detecting changes in the response of metal oxide (MOX) gas sensors deployed in an open sampling system is a hard problem. It is relevant for applications such as gas leak detection in coal mines [1], [2] or large scale pollution monitoring [3],[4] where it is unpractical to continuously store or transfer sensor readings and reliable calibration is hard to achieve. Under these circumstances it is desirable to detect points in the signal where a change indicates a significant event, e.g. the presence of gas or a sudden change of concentration. The key idea behind the proposed change detection approach is that a change in the emission modality of a gas source appears locally as an exponential function in the response of MOX sensors due to their long response and recovery times. The proposed method interprets the sensor response by fitting a piecewise exponential function with different time constants for the response and recovery phase. The number of exponentials is determined automatically using an approximate method based on the L1-norm. This asymmetric exponential trend filtering problem is formulated as a convex optimization problem, which is particularly advantageous from the computational point of view. The algorithm is evaluated with an experimental setup where a gas source changes in intensity, compound, and mixture ratio, and it is compared against the previously proposed Generalized Likelihood Ratio (GLR) based algorithm [6].

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The proposed algorithm is inspired by the piecewise linear trend filtering proposed in [5]:

$$\underset{x}{\text{minimize}} \|x-y\|_2^2 + \lambda \|DDx\|_1 \tag{1}$$

where y is the sensor response, x is the trend to be estimated, and D is the matrix operator that calculates first order differences. $\lambda \geq 0$ is a regularization parameter used to control the trade-off between the magnitude of the residuals $\|x-y\|_2^2$ and the smoothness of the signal encoded by $\|DDx\|_1$. For the case of piecewise linear filtering, smoothness is encoded as minimization of the second derivative DDx, which for a line is exactly equal to zero. It is important to notice that the L1-norm is used to induce sparsity in the smoothness term and therefore to obtain a function which is "mostly linear" with few sharp kink points. In this paper we propose to model, instead of a piecewise linear trend, a piecewise exponential trend for capturing the sensor response induced by abrupt changes in the emission of the gas source. The kinks between subsequent exponentials in the estimated trend are interpreted as change point candidates. Exponential decays are characterized by the relationship $dx/dt = -\tau d^2x/dt^2$ where τ is the time constant of the exponential function. Therefore the exponential behavior can be encoded as $\|(I+\tau D)Dx\|_1$. However, MOX sensors have two different time constants for the response and recovery phases. In order to account for this, we introduce additional variables and constraints obtaining the following optimization problem:

$$\begin{aligned} &\underset{x,d_+,d_-}{\text{minimize}} && \|x-y\|_2^2 + \lambda\|(I+\tau_+ D)d_+\|_1 + \lambda\|(I+\tau_- D)d_-\|_1 \\ &s.t. && d_+ \geq Dx \quad d_+ \geq 0 \quad d_- \leq Dx \quad d_- \leq 0 \quad d_+ + d_- = Dx \end{aligned} \tag{2}$$

where τ_+ and τ_- are the time constants of response and decay. The variables d_+ and d_- and the corresponding linear inequality constraints were introduced to model the derivative of the trend for response and decay phases. The resulting optimization problem is convex, and therefore can be solved efficiently and is guaranteed to find the global optimal solution.

RESULTS

The proposed change point detection algorithm is evaluated on 54 indoor experiments where a gas source was placed 0.5m upwind an array of 11 commercial MOX gas sensors. In these experiments, the gas source emits ethanol and/or 2-propanol. The experiments include different characteristic gas emission profiles with changes in concentration, compound and mixture and provide ground truth for the change times. Fig. 1 (left) shows the receiver operating characteristic (ROC) curve for a selected MOX sensor, calculated using all the experiments and Fig. 1 (right) shows one example execution of the proposed algorithm for an experiment where the gas source presents changes in concentration of ethanol.

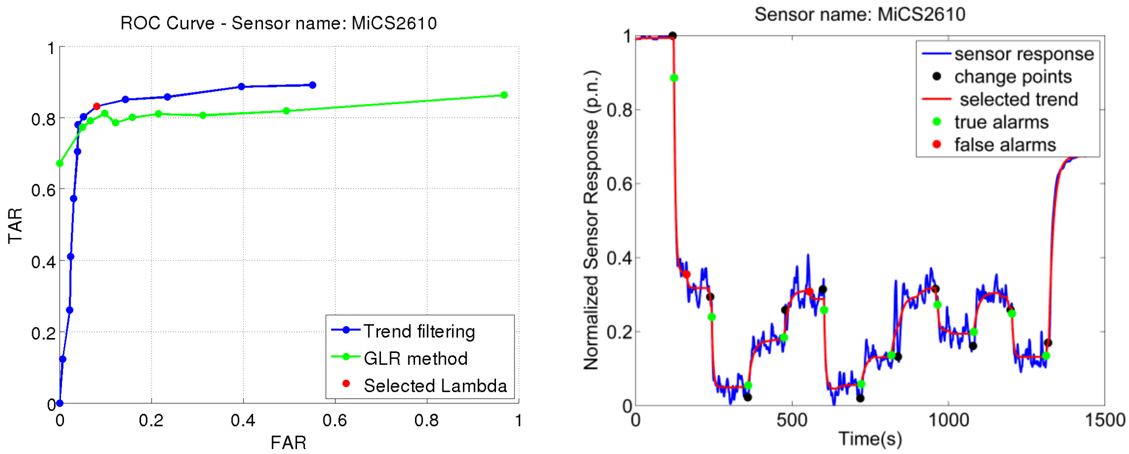

Figure 1. Left: ROC curves for the trend filtering and the GLR method for different values of the λ parameter (trend filtering) and detection threshold (GLR method), respectively. Right: example result of the proposed trend filtering method for λ=4 (indicated by a red dot in the left plot) representing a good true to false alarm tradeoff.

We compared the proposed trend filtering method to the GLR method [6] using the true alarm ratio (TAR) with the false alarm ratio (FAR) set to 0.1. The proposed method achieved a better performance for 6 out of 11 sensors in comparison to the GLR method (Table 1) using an automatically selected parameter λ, and is computationally more efficient since it scales linearly with the number of samples instead of quadratically like the GLR. Moreover, as can be noticed in Fig. 1 (left) the parameter λ allows a better control over the FAR/TAR tradeoff with respect to the detection threshold used by the GLR method.

Table 1. True alarm ratio (TAR) obtained when the false alarm ratio (FAR) is set to 0.1 for the single sensors.

	MiCS 2610	MiCS 2710	MiCS 5521-1	MiCS 5121	MiCS 5135	MiCS 5521-2	TGS 2600-1	TGS 2611	TGS 2620	TGS 2600-2	TGS 2602
GLR	0,81	0,83	0,59	0,76	**0,84**	**0,69**	0,61	**0,71**	**0,61**	0,6	0,41
l1-exp-trend	**0,84**	0,83	**0,62**	**0,77**	0,82	0,66	**0,66**	0,66	0,6	**0,63**	**0,49**

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