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Automatic fault identification and on-line unsupervised calibration of replaced sensors by means of cooperative classifiers

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Abstract

In this paper, we present a data processing architecture based on a set of cooperative classifiers aimed at class recognition with sensor arrays. The main property of the method is the mitigation of the performance degradation due to drift and fault of individual sensors. Moreover the capability to preserve high classification rate even with a faulty sensor allows replacing and calibrating a sensor during the measurement itself. The algorithm has been positively tested with an experimental dataset with an array of commercial metal oxide semiconductor sensors used to identify a number of volatile compounds.

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Keywords: sensor drift; sensor fault; online calibration.

1. Introduction

Drift and fault are dramatic events which change the initial relationship between sensor output and input stimulus. The former generally is a degenerative phenomenon altering both sensitivity and cross-selectivity of a sensor. Despite this mutation, the class differences can be preserved using appropriate signal processing and classification models [1,2]. On the other hand, fault is a catastrophic event where the output is no more correlated with the input. Because of this, discrimination is no longer possible and

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the removal or replacement of faulty sensor is then required for restoring the original performances. When a single sensor is used for classification, the sensor replacement is straight procedure that consists in implementing the new device with its own model. Unfortunately one sensor is often no adequate to handle complex discrimination tasks and a system based on array of partial selective chemical sensors can be then preferred [3,4]. Because of information redundancy in the system, the sensor arrays can show an intrinsic tolerance to both drift and fault events considering the classification purpose. Nevertheless in a sensor replacement scenario, the differences among nominally identical sensors make necessary renewing of the data analysis model. To overcome this limitation, in this paper we report how to perform an online calibration of a new sensor by mean of a versatile classification model able to counteract also sensor drift (Fig. 1).

**Fig. 1:** Architecture of the classifier. The features extracted by the signals of the sensors concur to build a classification sub-model proper for each sensor. Each classifier contributes to final class assignment of new sample by means of a Discriminant Scores vector. The sample is assigned to the class for which the highest sum of the Discriminant Scores is achieved.

2. The classification architecture

The model, shown in fig.1, is a global classifier formed by a set of adaptive-classifiers each of which is trained with the data of its relevant sensor [5]. In this way every model composing the array is independent from the others. Throughout test phase, the Discriminant Score (DS) vector is estimated for each sub-model and subsequently used as weights in a majority voting decision rule aimed to assign the global class. Finally this latter class is used for adapting the sub-models templates to be able in following sensor drift.

It has been already demonstrated the effectiveness of model in mitigating both drift and fault in [5]. In this paper we want to show the system capability in calibrating a new sensor during the test itself in order to substitute his replica in the array.
The main steps of the algorithm are outlined in figure 2. The fault event is unsupervisedly detected from each sub-model by a comparison of the DS values of the last measured sample with those obtained with the previous samples by the same sub-model. When the DS of different classes are close among them for several samples, the fault is detected. After a positive detection, the faulty sensor has to be replaced into the array with a new sensor of the same kind. Remarkably since the sub-models are independent it is possible to remove and replace the single classifier from the ensemble without dealing with the others. During the calibration phase the new element does not participate actively to classification even though its responses have been recorded. In order to train the sensor model, each measurement has to be associated to a proper label. To preserve the unsupervised way of the calibration procedure, in this case the class assignments of the whole array have been paired with new sensor data. After the collection of a sufficiently exhaustive training set, the sub-model of the replaced sensor can be created and admitted to contribute to the class assignment together with the other models.

3. Experimental Results

The features of the algorithm have been validated considering an experiment where an array composed by several replicas of four sensor kinds has been exposed to three different kind of sample each consisting in a pure Volatile Organic Compound (VOCs) diluted at a fixed concentration [6]. The initial dataset is related to subset of only four sensors, one for each sensor kind. The remaining replica data have been collected so that they could be used in the algorithm to simulate the replacement of the faulty sensors. The dataset, affected by drift, is composed by 300 measurements where the initial 60 samples have been used to train the single sensor models and the other 240 to validate it. To investigate the potentialities of the proposed algorithm, artificial faults were induced setting the sensor response to zero.

As shown in Fig. 3, the adaptive behavior of models allows reaching an almost perfect classification rate (99.16%) when no fault is occurred in the sensor array.
Fig. 3: Comparison of the classification rate of the proposed architecture with different sensor faults and after the sensor replacement obtained in the testing phase.

Secondly a fault has been simulated setting the sensor output to zero after 90 test samples till the end of dataset. In each simulation only a single sensor fault has been considered. In this case a reduction of classification rate occurs even if in the worst case it is slightly below 90%. Even if the DS can mitigate the decrease of performance, the difference is still significant but the classification rate is anyway high. It is worth to note that fault tolerance is extremely important for a correct training of the replaced sensor model. For this reason if the classification rate during its calibration phase is too low, the new model train will be compromised. A comparison of the global performance of the algorithm with and without sensor replacement is shown in Fig.3. In all the considered cases, the algorithm exhibits a substantial improvement of the classification rate proving the benefits of the online calibration.

4. Conclusions

In this work, we have illustrated an algorithm for on-line unsupervised calibration of a new sensor. The experimental data have confirmed the potentials of the proposed approach. Further studies will investigate the performance of this architecture when and additional class is considered during the testing phase adding also a new sensor kind to the array.

References