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Electronic Nose as an NDT Tool for Aerospace Industry

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Abstract

Artificial olfaction is an emerging technology aiming to develop tools for easy, rapid and mobile gas mixture analysis. So far, its application to several application fields is under investigation with some commercial solution already deployed. In this work we present the results of the development process for an electronic nose devised for NDT in aerospace industry focusing on its pattern recognition stage.

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Keywords: Electronic Nose, Pattern Recognition, Non Desctructive Tests, Aerospace Industry.

1. Introduction

Electronic noses are biomimetic tools that can be defined as intelligent chemical multi-sensors devices. They have been applied to several application fields with the goal of providing chemical mixture detection, identification and quantification capabilities (Pearce et al., 2007). Mimicking the basic structure underlying mammals olfaction, they are built on a three layer architecture with the first stage being represented by a sampling system, the second being a chemical sensor array, and the third being a pattern recognition system. The chemometric capabilities expressed by such a compact tool is actually considered relevant for applications in medicine (Di Natale et al., 2003), environmental monitoring (De Vito et al., 2009; Mead et al., 2013), food industry (Bianchi et al., 2009)**Error!**

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Reference source not found., security, as witnessed by the number of scientific papers that contributed to the development of several ad-hoc tools (Rock et al., 2008; Wilson and Baietto, 2009). Diffusion of e-nose technology, however, is hindered by fundamental issues, often related with solid state chemical sensors limitations such as sensors drift, lack of specificity and sensibility to environmental conditions, and by operative conditions that fails to meet requirements of the application market (Padilla et al., 2011). NDT tools are specifically developed whenever a qualification test is needed to be performed on parts without affecting their working capability. Aerospace industry strongly relies on NDTs to guarantee safety and efficiency of their production. One of the most important challenge concern the development of the so called green aircraft by using light weight composite materials (CFRP – Carbon Fiber Reinforced Polymers) that are assembled by adhesive bonding. However, the lack of validated methodologies for the evaluation of the assembly quality limits the adoption of such materials in primary aircraft structure. Surface contamination is crucial for safety of the bonds (see Markatos et al., 2013; Markatos et al., 2013b) a contaminated surface significantly affect the mechanical strength of the CFRP panels adhesive bond and may occur by different liquid contaminants such as hydraulic fluids, runway deicing fluids, moisture, release agents, etc. The development of a NDT able to assess contamination state of the surface in terms of identify and quantify contaminants is therefore mandatory for the development of the green aircraft technology. With its characteristics, e-nose technology can represent a solution for this problem, but several adaptations and careful sensor array selection should be applied to obtain results in this rather unusual scenario for an electronic nose. In facts, rapid, on-field surface analysis is itself rarely addressed by artificial olfaction researchers (D'Amico et al., 2008). Quantification capability is also relevant to understand if the panels under analysis could qualify for adhesive bonding or should undergo a further cleaning process or being discarded. Reliability, rapid response, portability, capability to deal with harsh are further, if not mandatory, requirements.
Pattern recognition is a key enabler for electronic noses capabilities, but commonly available methods cannot deal with the rather peculiar response of chemical sensors and with the requirements of e-nose applications. In this paper, we show the current results of the effort spent in developing an ad-hoc pattern recognition solution for an e-nose dealing with CFRP surface analysis task.

2 Experimental Setup

2.1 Samples Contamination scenarios

Three different contamination scenarios including hydraulic fluids, release agents and moisture at three contamination levels were investigated. The selected hydraulic fluid has been Skydrol® (500B4), one of the most popular fire resistant aviation fluid. Skydrol® reaction with water releases phosphoric acid and alcohols that can undermine the CFRP structure. Release agents causes silicone contamination which can penetrate up to hundreds of nm into the matrix of the CFRP panel and can prevent an effective adhesive bonding. To simulate release agent contamination, clean CFRP samples were dip coated with solutions of a release agent (Frekote 700NC) at different loadings.
CFRP adhesive joints have been found to be sensitive also to the presence of moisture and thus four different levels moisture uptakes were considered in this work according to the exposure to four relative humidity conditions (RH 100%, 95%, 75%, 30%). The water uptakes were then evaluated by the mass increase of CFRP samples with respect to the dry ones.

2.2 Sensor Array and E-Nose Platform

The relevant dataset has been captured by analyzing the CFRP sample set using the Airsense GDA2 electronic nose. This e-nose is built around a hybrid sensor array based on two Metal Oxide Chemical sensors (MOX), one Electrochemical sensor, one Photoionization detector (PID) and one Ion Mobility Spectrometer. All the sensors but the IMS have a response characterized by a single value per instant of time while the IMS response is a time of flight (TOF) based spectra like response that allow for an enhanced discrimination capability. The IMS spectra has been processed to extract descriptive features based on the area under the spectra curve over peculiar TOF regions.

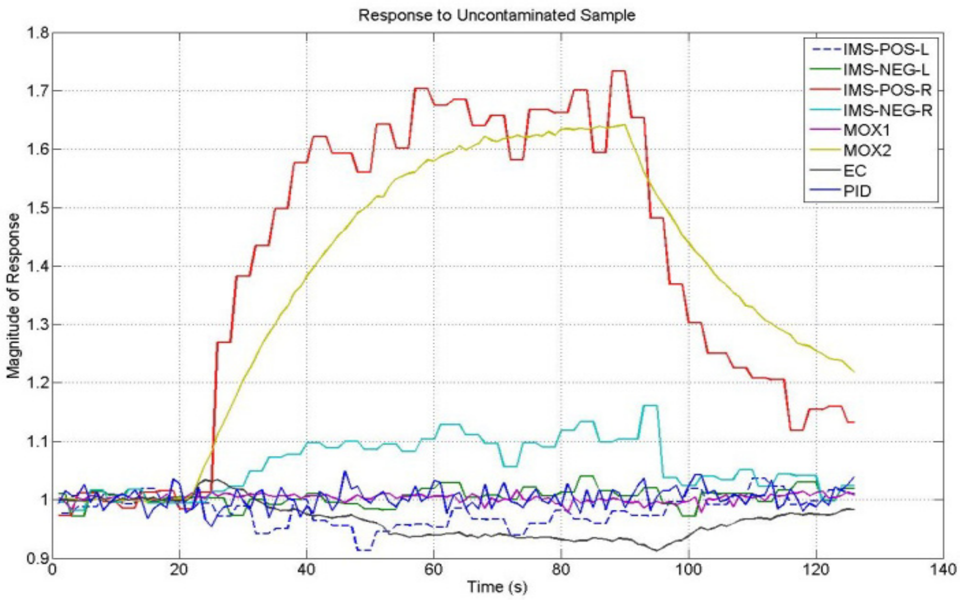

Figure 1: GDA 2Electronic nose response to a measurement cycle of an untreated (UT) sample featuring the reponse of the single sensors and the integral features extracted frm the IMS response.

2.3 The Pattern Recognition design

The contamination detection and identification task can be described as a classification problem in which the electronic nose architecture is bound to produce a classification estimation allocating the CFRP sample under analysis to a specific label within the set:

[UT,SK,FR,MO]

with UT being the label corresponding to a clean sample, SK corresponding to a Skydrol contaminated sample, FR corresponding to a Release agent contaminated sample and MO corresponding to a Moisture contaminated sample. In order to fulfil the scenario requirements, a fast response should be provided while keeping accuracy at the highest level. For this reasons, our design foresees a two stage pattern recognition system. The first one is concerned with a rapid, sample by sample analysis and consequent identification of the contamination state (detection and discrimination of the contaminant). The second one is concerned with an high accuracy assessment of the overall response using the combined response of the sample by sample stage throughout the measurement cycle.

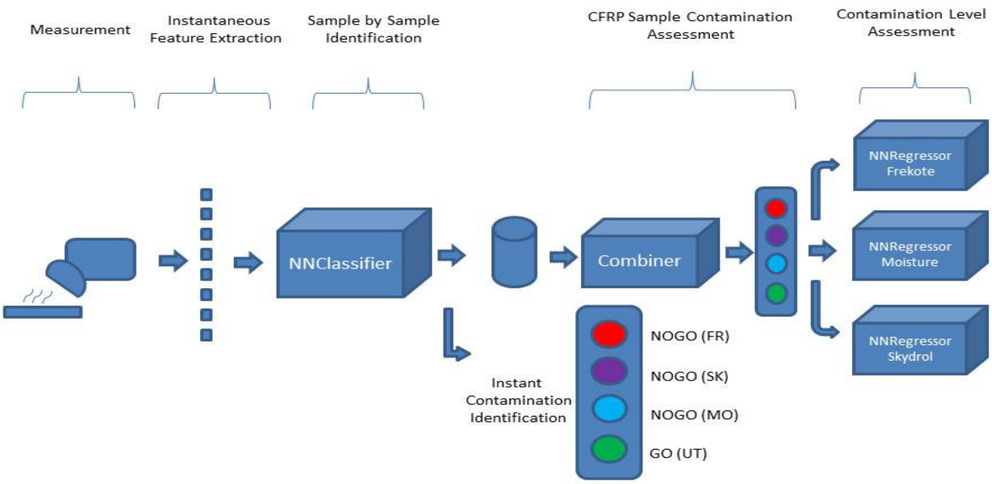

Figure 2: Pattern Analysis and Recognition Architecture

The core of the computational intelligence system is based on an Artificial Neural Network classifier designed for identification for the contaminant and on a neural regressor designed to estimate the contamination quantitatively. The classifier will also provide a simple measure of the sample-by sample classification reliability while at the end of the measurement cycle the average accuracy and the number of samples classified as belonging to a contamination specie will provide an overall reliability measure. Finally a quantification estimation is provided. Here we focus on the detection and discrimination problem.

In order to efficiently train the supervised classifier, the sensor responses of the labelled measurement dataset have been collected and the relevant sample have been extracted. A single measurement cycle response (see Fig. 1) have been divided in different time intervals, i.e. the injection-transient phase corresponding to samples belonging to the [15s, 30s], the steady state response phase corresponding to [30s, 100s] and the desorption phase corresponding to [100s, 120s] interval. Sample belonging to injection-transient and steady state intervals have been selected to become part of the PARC dataset. Collected samples have been labelled and samples belonging to a percentage of the measurement cycles have been extracted to become part of the training set while the remaining samples have been used for testing purposes. The partition procedure has been repeated for 100 time and hence, performance have been estimated with a 100-per cross validation approach.

3. Results and Discussion

Sample-by-sample estimated performances, reach 69% of correct classification rate and can be defined as encouraging, but unfortunately, the distribution of wrongly classified across different CFRP samples is far from uniform, with these samples being substantially related with only a subset of the CFRP samples of the dataset. This prevent to obtain 100% accuracy by cycle wide combination approach. In facts, in order to obtain a cycle wide estimation we tested for the execution of two different combination procedures, i.e. a sample by sample majority vote and an accuracy mediated majority voting. For majority voting, class labelling reliability A'_{Class} has been estimated by dividing the number of votes for each class for the number of total relevant samples in the measurement cycle. As regards as the second approach, a labelling accuracy have been computed for each class by using the following equation:

$$A''_{Class} = \sum_{i=1}^{k_{class}} NNOut_{i,Class}$$

Where $\mathrm{ANNOut}_{\mathrm{i,Class}}$ is the i-sample neural network output value for the neuron corresponding to the class under estimation.
The CFRP sample under analysis is hence labelled with label obtaining the maximum $\mathrm{A}_{\mathrm{Class}}$ accuracy. These indexes can be computed with a running real time approach providing an on-line approximation of cycle-wide classification accuracy.
Adopting a cycle wide combination approach, with a majority vote approach, the cycle wide classification performance can be estimated in 71.5%, while adopting the sample by sample accuracy mediated majority vote hold for a 72.2% correct estimation rate.
A false negative performance of 5.2% is interesting considering the high cost of such a misclassification in the safety critical scenario in which this work is aimed, however, the false positive rate is still too high to be considered as satisfactory (25%) and need to be improved.

4. Conclusions and future works

In this paper we have shown how the pattern recognition system of an electronic nose technology can be designed to address a rather demanding industrial scenario with fast assessment requirement. Achieved performance levels have found to be interesting with respect to end users perspective. Current results make us confident that improvement in both false negative and true positive rate could be achieved by introducing a reject option, i.e. introducing a way for the cycle wide classifier to reduce errors by refusing to cast a labelling estimation for CFRP samples that it cannot classify confidently.
The electronic nose is hence showing the capability to potentially become a suitable tool for safety critical scenarios as a first line, low operative costs tool to trigger the use of more cost intensive analytical tools.

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