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Combining Real Time Classifiers for Fast and Reliable Electronic Nose response analysis for Aerospace NDTs

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Abstract

Fast response and reliability are a prerogative in non-destructive tests specifically in aerospace industry for safety and efficiency reasons. Currently, composite panels bonding, in green aircraft concept, is lacking a validated NDT technique for the bond quality. E-noses equipped with PARC algorithms appear a promising choice to acquire speedily a complete pattern response maximizing reliability. In this paper, combining real time classifiers, we show how to obtain a rapid first-hand response with the possibility of increasing accuracy awaiting for the end of the e-nose measurement cycle. A reject option is casted on the base of classifier self-perceived reliability to nullify false negatives while keeping the false positive rate at minimum.

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Keywords: Electronic Noses, Industrial Applications, Aerospace Industry, Hybrid sensor arrays, Ion Mobility Spectrometers, Surface analysis;

1. Introduction

NDT tools are specifically developed whenever a qualification test is needed as in assembly or maintenance operations in aircraft safety and efficiency. Specifically, in order to limit costs and carbon footprint of air transport, light weight composite

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materials (CFRP – Carbon Fiber Reinforced Polymers) are adopted. Their usage may also account for a reduction of per-mile-passenger transport costs up to 15%. Actually a fundamental limit to a wider adoption of such materials is the lack of validated methodologies for the assessment of the assembly quality, i.e. surface cleanliness before bonding. In facts, surface contamination significantly affects the mechanical strength of the CFRP panels adhesive bond either limiting adhesion performance by physical screening or chemical action on the surfaces. Contamination may occur in several moments in aircraft assembly or operative life by different liquid contaminants such as hydraulic fluids, runway de-icing fluids, moisture, release agents, etc. Recent findings (e.g. Markatos et al. [1]) show that contamination by hydraulic fluids may severely reduce the mode I fracture toughness (G1C), a relevant mechanical parameter for adhesive bonding, up to 25% for Skydrol500-B contamination and up to 60% with regards to release agent contamination.

Among NDT technologies, electronic noses seem particularly promising to be used for detection and quantification of surface contamination for their potential low cost, relative responsiveness, portability, and most of all the possibility to be used by personnel that do not enjoy an ad-hoc artificial olfaction training. In facts, e-noses are intelligent chemical multi-sensors devices that have been applied to several application fields where chemical mixture detection, identification and quantification are concerned [1]. The chemo metric capability expressed by such a compact tool is actually considered as relevant for applications in medicine, environmental monitoring [3], food industry. On the other hand, e-nose several adaptations and careful sensors and model selection should be applied to obtain results in this rather unusual scenario without a strict control on environmental variables. Quantification capability is also relevant to understand if the CFRP panels under analysis could qualify for adhesive bonding or should undergo a further cleaning process or being discarded.

In this paper, we describe the effort and results of screening, adapting and testing electronic nose technologies for their application in the non-destructive testing of CFRP bonding in aerospace industry particularly seeking for pre-bonding identification and quantification of relevant contaminants on CFRP surfaces.

2. Experimental Setup

The CFRP material is a thermoset matrix with carbon fibres arranged in UD layers (HexPly© M21 matrix from Hexcel and T700 low density carbon fibres). In our experimental setup, three different contamination scenarios in, at least, three contamination levels were investigated: hydraulic fluids (Skydrol 500-B4), release agents (Henkel Frekote 700-NC) and moisture. They have been tagged respectively as SK, FR and MO, while UT is untreated samples' tag. Untreated and contaminated samples off-gas have been directly measured by means of the Airsense GDA2 electronic nose an hybrid multisensing device relying on a 2 MOX, 1 EC, 1 PID and an IMS sensor.

2.1 Chemical characteristics of the contaminants and Samples Contamination procedures

The hydraulic fluid used is Skydrol® (500B4), one of the most popular fire resistant aviation fluid made up of a group of chemical additives dissolved into a fire-resistant phosphate ester base. In contact with water, Skydrol® releases phosphoric acid and alcohols that can undermine the CFRP structure. In this work, the contamination levels were referred to the pH of an aqueous extract of Skydrol®. CFRP samples were actually immersed in Skydrol®-water phase solutions at pH 2, pH 3 and pH 4 for 672 hours in an oven at 70 ºC. Release agents containing silicon are used for the moulding process of composite panels. The silicon concentration on the CFRP surface can then be typically in the range of 5 to 20 %. To our purposes, clean CFRP samples were dip coated with solutions of release agent at different loadings. Thus, four Si residue levels, covering the above mentioned range (namely 4 atom%, 8 atom% and 10atom%) were investigated herein by XRF. 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%). Samples were exposed to demineralised water and to saturated aqueous solutions of K_2SO_4, NaCl and $MgCl_2$ for 672 hours at 70 °C. The water uptakes were then evaluated as contamination index with respect to the dry ones.

2.2 Pattern Recognition S/S design

This specific contamination detection and identification task can be described as a classification problem in which the e-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]. The PARC architecture should be able to provide a fast response on the contamination state of the surface under analysis with the highest possible reliability level. To meet this requirement, our design encompass a two stage pattern recognition system. The first one is concerned with a rapid, sample by sample analysis and simultaneous identification of the contamination state i.e. with the detection and discrimination of the contaminant. The second one is concerned with the assessment of the overall e-nose response using the combined findings of the sample by sample stage throughout the entire measurement cycle. The core of the computational intelligence system is based on an Artificial Neural Network classifier designed for identification for the contaminant. The first stage classifier will also provide a measure of the sample-by-sample classification reliability while, at the end of the measurement cycle, the average reliability and the number of samples classified as belonging to a contamination specie will provide an overall reliability measure. Finally a quantification estimation is provided by analysing the average response of a sample by sample neural regressor. In such a way, the operator will be able to obtain a fast response from the electronic nose architecture considering that a stable response could be quickly dispatched while he could wait to the end of the measurement cycle to obtain a maximum reliability response in the doubtful cases when the sample by sample response is oscillating among multiple labels.

3. Results

In order to efficiently train the supervised classifier and regressor, the sensor responses of the labelled measurement dataset have been collected and the relevant sample have been extracted.

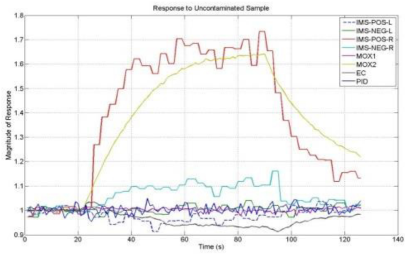

Fig. 1 Electronic nose response to a measurement cycle of an untreated (UT) sample.

Specifically, a single measurement cycle response have been divided in different time intervals (Fig. 2), 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. The dataset is composed by 40 total different measurements related to 10 composite panels, for amount of 4400 samples represented by the instantaneous response of all the solid state sensors and a bucketing partition of the AuC (Area under the curve) of the positive and negative IMS spectra. Collected sample have been labelled and samples belonging to a percentage of 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 have been in order to pursue a 100x cross validation approach to performance estimation. Sample-by-sample correct classification rate of the trained classifier was 68%, in the range to be defined encouraging. 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 a sample by sample reliability mediated majority voting. Once the winner class, i.e. the one receiving the highest number of sample by sample classification votes, has been established, class labelling reliability CR' has been estimated, by dividing the number of votes of the winner class for the number of sensor array readings for every measurement cycle.

In the latter case, a class labelling reliability have been computed for each class j in [UT, FR, SK, MO] by using the following equation:

$$CR''_{ij} = \sum_{i=1}^{k} ON_{ij}$$

where ON_{ij} is i-sample neural network output value for the j-th class and k is the number of sensor array readings. The class

obtaining the maximum CR''_{ij} evaluation represent the winner class.
Note that both measure can be, in principle, computed with a running real time approach providing an on-line approximation of cycle-wide classification reliability. In both cases, a cycle wide performance estimation produces a correct classification rate of 70%, with a fp and fn rate, respectively, of 21% and 5%, still unsatisfying for the specific application.

3.1 Rejection option

Further improvement in both false negative and false positive 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. By an analysis of the distribution of cycle wide reliability with which the cycle wide classification occur both for correct classification events and misclassification (Fig. 3), it can be noted that misclassification occurs at highest rates when estimated reliability is low. Exploiting this simple statistical finding, it is possible to empirically set a threshold on combined classifier perceived reliability, so to identify CFRP samples that are difficult to classify leading to a misclassification error. An increase in the size of the dataset could actually lead to the implementation of a fair procedure for optimal and automatic choice of the threshold level. Once the threshold is set up, the performance estimators change their values significantly. For example, setting threshold value to 0.6, we obtain a reject rate of 21% while fp rate settle at 20% , a fn perfect score equal to 0%, and correct classification rate reach 78.5%. At a threshold value of 0.65, i.e. with a reject rate settle at a value of 35%, we obtain a fp rate of 8% and a correct classification rate of 84% while

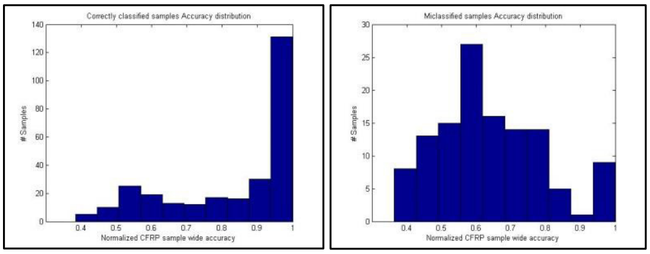

Fig. 2 Accuracy frequency distribution among analysed CFRP samples

4. Conclusions

In this paper we have shown a PARC procedure to obtain a fast and reliable e-nose assessment. A reject option approach allowed for the improvement of overall performance at the cost of refusing low classification confidence samples. Result supports the potential application of e-nose to the critical issue of surface contamination identification in the pre-bonding phase of CFRP samples.

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