Detection of Moulds Growing on Building Materials by Gas Sensor Arrays and Pattern Recognition

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Summary: *This work explores the detection of moulds growing in different building materials by using a metal oxide sensor array Four mould species have been considered. Pattern Classification provides classification rates on the order of 80-90% for different species. Drift degrades slightyl these values subsequent test four months later.*

Keywords: *moulds, sensor arrays, pattern recognition*

1 Introduction

Excessive humidity and subsequent fungal development are one of the most frequent problems in buildings. Moulds can produce allergies, infections and toxic effects. The detection of MVOCs (microbial volatile organic compounds) seems particularly interesting because the compounds can penetrate barriers the spores can not, facilitating the detection of hidden moulds. The detection of these compounds has been previously addressed by Gas Chromatography- Mass Spectrometry. Moulds produce a wide range of MVOCs: alcohols, ketones, terpenes, esters and sulphur compounds. The production depends on environmental conditions and the substrate on which the fungi grow. However, no single VOC seems to be a reliable indicator of biocontamination [1]. For this reason fungal detection can not be based on a single substance but on the coexistence of several compounds.

The authors have already addressed the detection of a single mould species, namely *aspergillus versicolor*, in a previous paper[2]. Here this work will be completed with more extensive measurements involving three additional mould species: *Penicillium Aurantiogriseum*, *Penicillium Chrysogeum and Cladosporium Sphaerospermu.* Fungal detection has been also previously addressed by Schiffman et al. [3].

2 Materials and Methods

Five different materials typical of Belgian houses were used as substrates for mould growing: plasterboard, particleboard, oriented strain board, wallpaper and glue. Some combinations of them were also analyzed. The four fungal species were incubated in Malt Extract Agar for one week. After this period, moulds were inoculated into the building materials. Contaminated samples were incubated in airtight glass jars (500 ml) closed with a Teflon cover. The jars were kept at room temperature in the darkness during the whole duration of the experiments.

The Gas Sensor Array was designed and constructed at the University of Liege. The sensor array contains 12 metal oxide sensors: six of them manufactured by Capteur, and six from Figaro.

For each fungal species, two sequential experiments were carried out, resulting in two datasets comprising the growth of the moulds during 4 months. Clean and contaminated materials (corresponding to different species) were randomly presented to the gas sensor array during this time.

3. Signal and Data Processing

The sensor signals were preprocessed by taking the ratio of the resistance at the end of the sampling period and the baseline resistance. In this way a 12 dimensional vector was assembled. However two sensors were removed because of deficient behavior observed by visual inspection of the sensor patterns.

Our primary objective was the binary classification of moulds and no-moulds disregarding the particular fungal species and the substrate material. For classification several algorithms were explored: k-NN, Fuzzy k-NN[4], Mahalanobis classifiers, and Gaussian Mixture Models. For feature extraction purposes PCA and LDA projections were explored.

In a binary classification, LDA only permits to projection to a single dimension. To increase the dimensionality of the projection we explored the use of pseudo-classes by combining moulds with the different substrate materials.

For validation of the classifier results the following strategy has been followed. First dataset (for each mould species) has been divided in two equally sized random partitions. One part has been used for classifier design and optimization while the second half is used for classifier testing . This process is repeated ten times and the best parameters in terms of average classification rate are retained. The second half used for validation.

In addition to single species classifiers, multiple species classifiers have also been considers. Moreover, the capability of a classifier to generalize to unknown mould species (not present in the training set) has also been explored.

Results

PCA projection seems to indicate that the classes are non-separable, non-gaussian and multi-modal.

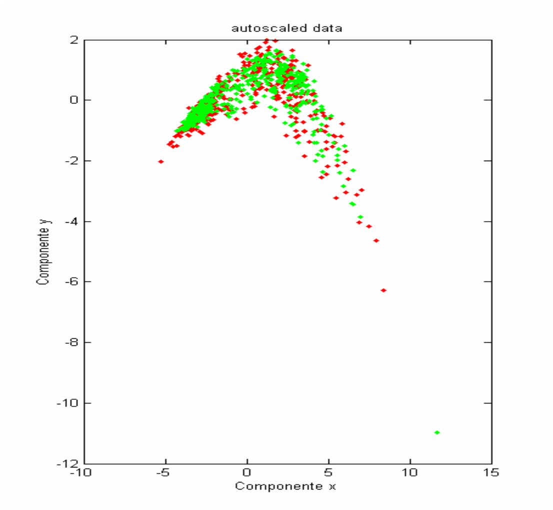

Figure 1. PCA projection: green contaminated samples, red clean samples.

Multi-modality clearly arises from the presence of different substrate materials. In fact, visual exploration of the results shows that the influence of the substrate is much larger than the influence of the presence of moulds. Due to the important background variability the detection of moulds becomes a difficult problem.

Best results are typically obtained with LDA projection plus Fuzzy-k-NN (k=3).

Table I: Classification rate for the 1st dataset

First set	auto
All moulds	87±1
penicillium chrysogenum	86±4
cladosporium sphaerospermum	92±2
aspergillus versicolor	87±2
penicillium aurantiogriseum	90±3

These results degrade slightly when the classifier estimated with the first dataset is used to classify the patterns from the second dataset. Note that every dataset has time duration on the order of four months. Results can be observed in Table II.

Table II: Classifier estimated in the first dataset applied to patterns from a second dataset.

second set on first set	auto
All moulds	82
penicillium chrysogenum	84
Cladosporium sphaerospermum	72
aspergillus versicolor	82
penicillium aurantiogriseum	87

The results although not extremely good in absolute terms have shown only a small degradation without any further recalibration of the system.

Finally the results show that the system has a certain capability to detect moulds from species not present in the training set. These results can be observed in this third table.

Table III: Classifier constructed with 3 mould species: Application to a fourth unknown one.

First set (3 moulds)	auto
Asper+clado+aur<-pcrys	79
clado+aur +pcrys<- asper	86
aur+pcrys+Asper < clado	85
Pcrys+asper +clado<-aur	79

Conclusions

The detection of moulds with an electronic nose is possible. However, background variability poses serious problems. On the positive side, the system shows only a slight degradation due to drift. Results also indicate that the system has a certain capability to recognize moulds not present in the training database. However, the system is prone to false alarms so in its present state it only shows potential for screening purposes.

References

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