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Lubricant Degradation Monitoring with AI-Assisted Sensors

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ABSTRACT

The value of machine lubrication is well understood, but all lubricants must be periodically tested to verify their condition. This has driven intense research towards the development of efficient, low cost and timely degradation monitoring solutions. However, the periodic testing currently used results in a difficult decision between the labour and downtime costs of testing more frequently and the risk of inter-inspection faults if testing is delayed.

A series of six metal oxide semiconductor gas sensors has been used within an artificial olfactory system (e-nose) to monitor the volatile compounds released by samples of mineral oil at different levels of thermal degradation. Data collected from the sensors has been used to train an artificial intelligence pattern recognition system based on principal component analysis and a support vector machine for both classification and regression predictions. The classifier achieved a 95.5% accuracy and the regression was accurate within a root-mean-square error of 2.47 showing the effective performance of an e-nose when applied to oil condition monitoring.

1. INTRODUCTION

Over the last decades the world has been transformed by increasing industrialization. As more countries develop their industrial base, there is a greater level of competition now than any point in history. Tribology as a field has grown since the landmark 1966 report which coined the term [1], and now its influence can be seen in almost every industry and aspect of society. An improved understanding of lubricant condition would allow an operator to maximise lifetime of equipment and minimise lubricant wastage.

When an organic lubricant degrades it is mainly through autoxidation. In this process, the carbon-carbon bonds are attacked by peroxide free radicals in a self-propagating chain-reaction and the bonds broken [2]. Over time this results in a shortening of the average chain length, changes in the functional groups, and the generation of volatile organic compounds (VOCs). Shortening of the chain length results in degraded lubricant performance, while the VOCs are released into the lubricant headspace [3]. Since the VOC composition must depend on the lubricant composition: a system may be developed which targets VOCs and reflects the lubricant condition.

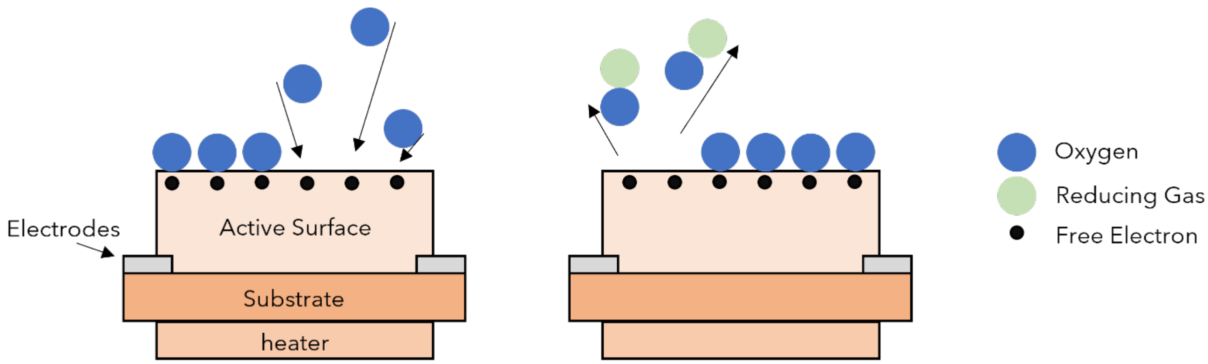

Figure 1. Function of a MOS gas sensor. As oxygen binds to the active surface its resistance increases; this resistance then decreases as reducing gases out-compete the binding sites.

One class of sensors commonly used to detect VOCs are the metal oxide semiconductor (MOS) conductometric sensors [4–6]. These are composed of 3 key components, as can be seen illustrated in Fig. 1. The MOS acts as an active surface which is mounted on a substrate and placed on top of a heater. When the substrate is heated, charge carriers collect on the surface of the semiconducting material and act as binding sites. If an n-type MOS is used, as is in the system discussed here, then the charge carriers are free electrons which bind to oxygen that reaches the active surface. The oxygen will remain on the active surface until a reducing gas removes it. The presence of a bound species on the surface causes a local depletion of charge carriers, and so generates a potential barrier that increases the resistance of the bulk MOS, which then reduces once the bound species is removed. The sensor response is the measurement of resistance across the active surface and follows a power-law relationship $R = \alpha P^{\beta}$, where R is the resistance, α a scaling constant, P is the partial pressure of target gas, and β is a constant defined by the active surface and the gas [7].

While a gas sensor can be used to measure the presence of a target gas, it is difficult to engineer a sensor that reacts only to the target. This cross-sensitivity is a major issue for gas sensors and great efforts are undertaken to try and limit this cross-sensitivity. Efforts to do this mainly focus on altering the sensor function through nanomaterials, catalytic, or biological treatments [8–10]. However, Persaud and Dodd showed in 1982 that a sensing device mimicking the mammalian olfactory system could be developed to analyse gases in a new way [11]. This time, an array of sensors is used which utilises the different cross-sensitivities of different sensors and an attached pattern recognition system to deduce the gases present. Such an artificial olfactory system is referred to as an e-nose. The authors have already conducted investigations to prove the effectiveness of an e-nose for lubricant condition monitoring [12].

Once a sensor response has been acquired the data is processed through a series of stages, as illustrated in Fig. 2. The first stage, pre-processing, aims to remove underlying effects on the sensors unrelated to the detection of VOCs. These effects are either differences in sensor scaling or changes in how the sensor responds over time (sensor drift). Feature extraction aims to turn the raw sensor response curves into descriptive data points (features) which are extracted from either the transient or steady state response. Features are collated and together become the feature vector which is then evaluated and unnecessary, redundant, or ineffective

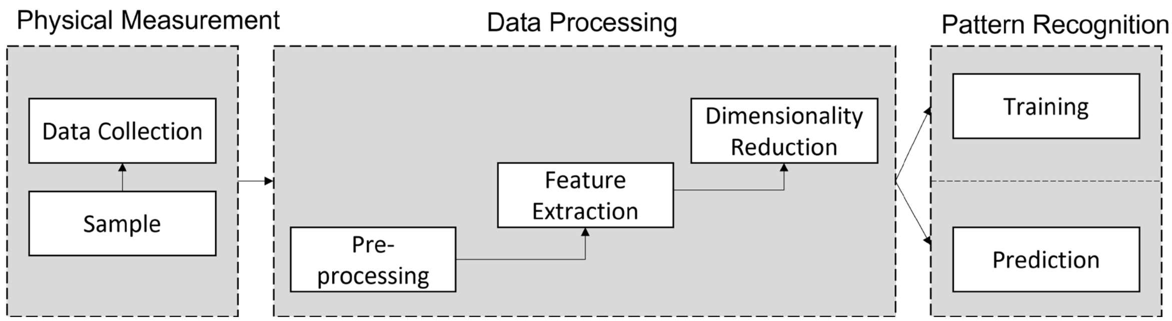

Figure 2. A diagram of the e-nose workflow.

features then removed. Correlated features may be removed using principal component analysis (PCA), a common statistical tool in the field of e-noses. PCA is an algorithm which uses the original features to define a new set which captures the maximum variance in as few variables as possible. Once a reduced feature vector is obtained, it is passed to a machine learning algorithm for either training or to make a prediction on an already trained algorithm [13,14]. For pattern recognition, support vector machines (SVMs) have seen a good amount of usage as the prediction tool for e-noses in recent years [15–17].

This report aims to highlight the potential for an e-nose to monitor the VOCs released by samples of thermally degraded lubricant and use pattern recognition tools to relate it to the original heating time the samples were subjected to. The longer term aim is to support the development of a system to automatically monitor the lubricant degradation due to tribological strains in a machine application.

2. METHODOLOGY

Quantities of 50 mL of mineral oil (Sigma-Aldrich, product code 330760) were separated into 3 bottles and heated on a hotplate at a constant temperature measured with a probe to be 160 °C. The heating ran for a range of times, 4 h, 18 h, 24 h. 5 mL and 10 mL aliquots of each heating time were transferred into specially made headspace sampling bottles for attachment to the sampling system.

A recirculating headspace configuration was used to transfer the sample headspace to the sensors. The recirculation minimises VOC loss ensuring measurement of the total VOC release of the mineral oil is taking place and not the VOC release rate – which may be slow given the long chain hydrocarbon solution that is the mineral oil. The configuration of the delivery system is illustrated in Fig. 3. The sensor array chamber was connected to the other components of the sampling system through a series of 4 mm polyurethane tubing connections.

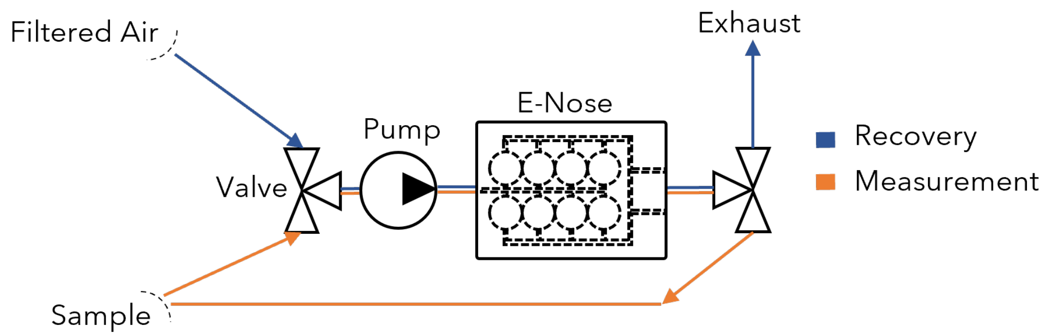

Figure 3. A schematic diagram of the experimental setup. There are two paths for gas to flow: filtered air is used during recovery and is immediately exhausted, sample air is recirculated between the sensor headspace and then back into the sample headspace. Note that the e-nose has eight but only six sensors are used.

Data collection was performed using an array of six gas sensors. All sensors are from the TGS series of MOS gas sensors from Figaro Engineering Inc. Details of sensor connections, readings, and the gas flow may be viewed in [12]. Control of the system was performed with an Arduino Leonardo microcontroller.

Due to the nature of the repeating redox reaction on the surface of the MOS sensors the sensor headspace must be exposed to an oxidising airflow to re-establish the baseline after measurement. The oxidising airflow was obtained by running the recovery path seen in Fig. 3. The recovery passes air collected from the external environment through moisture and hydrocarbon traps. The recovery path was active for 750 s after each lubricant measurement period of 150 s (a 15 min total cycle time).

Following the procedure set out in Fig. 2 the sensor response curves, once obtained, were pre-processed. First, the recovery phase was removed completely from the curve – then each of the individual measurement curves was normalised to between 0 – 1. That is to say that the corrected value, g, follows:

$$g = \frac{f - f_{MIN}}{f_{MAX}} \tag{1}$$

Where f is the uncorrected curve, f_{MIN} is the minimum response value for each cycle, and f_{MAX} is the maximum response value for each cycle.

Once the measurement curves were fully pre-processed, the features were extracted and passed to PCA for the feature reduction. The features were calculated on each of the six sensor and were: mean response, response range, time taken for 50% of response range, and the response value at time 5 s, 15 s, 30 s, 60 s, 90 s, 120 s, and 140 s. PCA reduced the original feature vector of 60 features into 11 principal component features. The reduced feature vector was used to train an SVM machine learning algorithm for classification and regression predictions. SVM's can use various kernel functions and for this analysis a quadratic kernel was applied. No separate test set was kept aside, instead a 5-fold cross-validation method was used to test effectiveness of the algorithm. This method splits the feature vector into 5 subsets and trains 5 independent algorithms – using each subset as a test set once – and then takes the

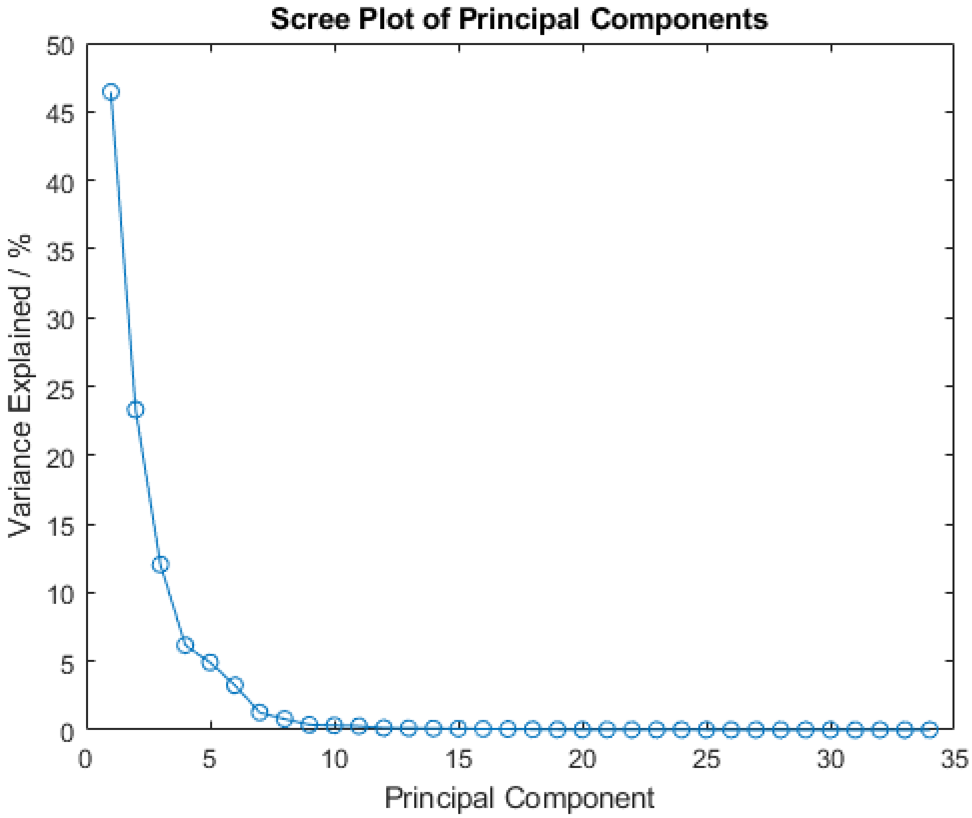

Figure 4. Scree plot for the explained variance of each principal component contributing over 0.1% variance. The total explained variance is 99.995%.

mean test error as the result. Additional testing has been performed which explore several combinations of machine learning algorithms and dimensionality reduction algorithms and will be published separately.

3. RESULTS AND DISCUSSION

Data was collected from the e-nose and predictions of lubricant heating time made. Both classification and regression algorithms have been tested and their performance compared. For both, the same feature vector was prepared and used for training.

The initial feature vector created from the measurement curves was processed through the principal component analysis (PCA) algorithm for feature extraction. 11 principal components were used which described a cumulative total of 99.995% of the variance. A scree plot illustrating the explained variance of each principal component contributing over 0.001% variance may be seen in Fig. 4. Prior to the PCA analysis, each feature in the feature vector was mean-centred and scaled to unit variance. The score plot for principal component one (PC-1) and two (PC-2) can be seen in Fig. 5. This score plot shows clearly that the data is statistically separable into at least four classes; PC-1 separates the four main classes and PC-2 appears to imply an additional grouping. The inclusion of multiple quantities was intentional and results in a trained algorithm which is more robust to changes in quantity of an unknown lubricant,

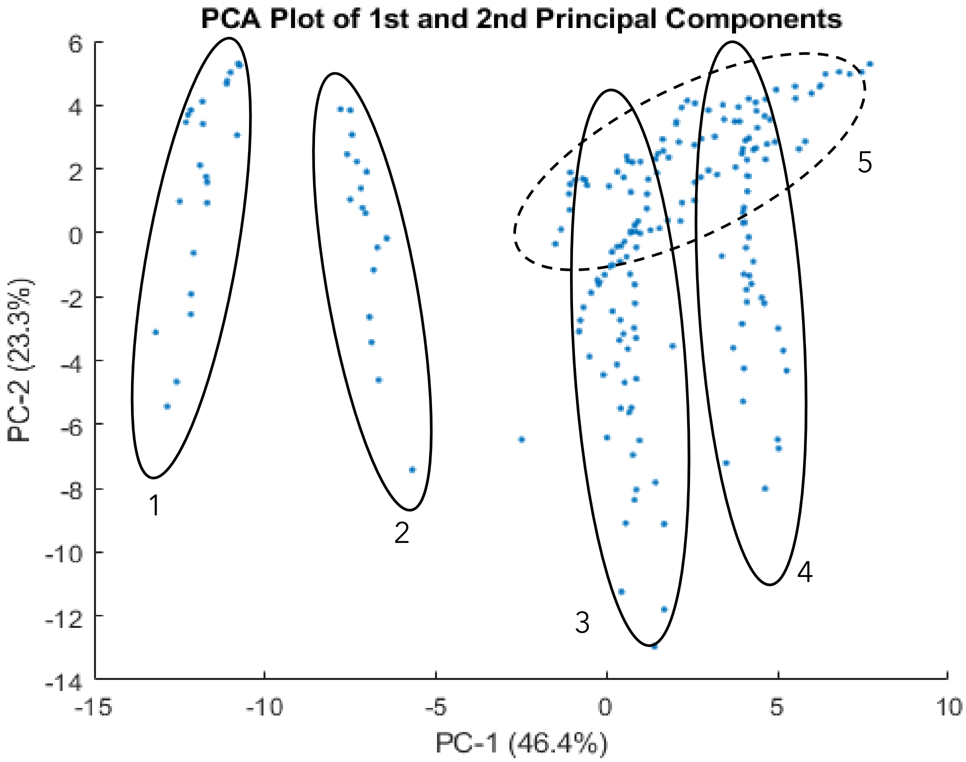

Figure 5. The PCA Score plot for the first two principal components. PC-1 is describing 46.4% of the variance and PC-2 is describing 23.3%. Four main groupings are labelled 1-4 and a fifth potential grouping labelled 5.

while making the current test performance weaker. Since PCA is used as a feature reduction method and is not used for pattern recognition it is important not to overemphasise the importance of extra groupings within these two principal components.

An SVM was then trained on the reduced feature vector. For an SVM classifier, a 99.5% validation accuracy was achieved using the 11 principal components and a quadratic kernel SVM. For a regression SVM, a RMSE of 2.47 h was calculated.

The oil samples studied were quite distinct in their visual appearance and so it is not unexpected that classification has a very strong performance. The lost 0.5% accuracy corresponds to a

single reading within the 24 h sample that was predicted to be a 18 h sample. The classification approach acts as a good demonstration the system's ability to discriminate the age of a lubricant via the VOCs it releases, but any practical application will have non-fixed heating times and so must rely on regression.

The regression approach is more challenging. Predicting a continuous variable will leave far more potential for error, while in classification the algorithm just needs to find the closest class. While the RMSE describes the total predictive error, another measure for the goodness-of-fit is the R-squared metric; a common statistical measure for how much variance is explained by the model. This model reached an R-squared value of 0.93, such that the model explained a very encouraging 93% of the variance in the features. The RMSE corresponded to 9.72% of the test range. If these results hold true for larger testing periods then the ability to discern an equivalent heating time of a lubricant to within 2.5 h would be an encouraging step on the path towards automating industrial maintenance.

4. CONCLUSION

The purpose of this study was to investigate the feasibility and effectiveness of monitoring lubricant health through artificial olfaction (e-noses). Predictions of heating time of a lubricant through analysis of the VOCs with an e-nose was performed with a 6-sensor array. PCA and an SVM were used in combination for dimensionality reduction and training of a classification and regression algorithm and the performance of those methods presented.
Classification achieved a 95.5% cross-validation accuracy, and regression achieved a RMSE of 2.47 and an R-squared value of 0.93. Both results suggest that an e-nose is effective at oil condition monitoring and the technology should be developed further. Since the technology is based within artificial intelligence pattern recognition, further testing expanding the size of the database and applying the system to new and similar applications will both improve performance and prove the robustness of the system.

While heating time is informative, it would be more useful to know the impact of specific tribological conditions of the lubricant. With that in mind work is currently being done to predict meaningful parameters of a lubricant as it degrades under mechanical operation through use of this same e-nose system.

Potential application of an effective e-nose sensing system for lubricant degradation monitoring includes manufacturing and transport. However, there are other applications where such a device would be revolutionary, they include energy generation, mining, aerospace, and other applications. Specific uses may include applications like space mechanism lubrication or other hard to reach places for maintainers where access to such an e-nose would provide an inexpensive and effective tool to inform decisions and prevent failures between ordinarily planned maintenance.

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