SoundCatcher: Acoustic Emission with Machine Learning for Monitoring of pMDI Adherence and Detection of Non-optimal Actuation Performance

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Abstract

In this study Acoustic Emission (AE) profiles, in combination with machine learning algorithms, have been used for patient adherence monitoring. The approach was evaluated in an experimental set-up designed to mimic a domestic environment. Three different technical configurations to produce non-optimal or unexpected actuations when using pMDIs as model devices were used. Using an image-based machine learning model with Convolutional Neural Networks (CNN) on the AE profiles highly accurate predictions were obtained, approximately 90%, of non-optimal actuations.

Introduction

- Passive AE monitoring is a cost-effective and non-invasive technology for quality and performance monitoring.[1-3]
- The aim of the project was to develop machine learning models for assessing adherence related attributes, such as unexpected or non-optimal actuations, when using pMDIs in a domestic-like environment.

Methods

Experimental

Analyses were made in an experimental set-up shown schematically in Figure 1. The design was chosen as to mimic a domestic environment with varying background noise. The output is raw sound files, as seen in Figure 2.

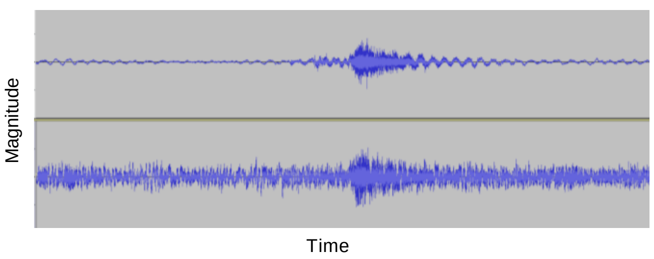

Figure 2: Example of a raw sound file from an inhalation – without (top) and with (bottom) background sound.

pMDIs filled with placebo formulation were used. Three different configurations, resulting in seven classes, were tested to simulate non-optimal actuation performance;

1) devices prepared with metering chambers of different sizes
2) devices with different orifice sizes
3) devices in which the orifice had been partially blocked through gluing

Data analysis

The raw sound files were first processed into spectral images, as seen in Figure 3.

Two data analysis approaches based on machine learning algorithms were then used for prediction of the inhalation configuration. The first approach was using multivariate analysis (MVDA) techniques and in the second data analysis approach CNN-models were used.

In both analysis approaches, the collected spectral images were manually split into a training/validation set (80%) and test set (20%). Models were then built based on the training/validation set, and reported results show the model performance on sound profiles from the test set.

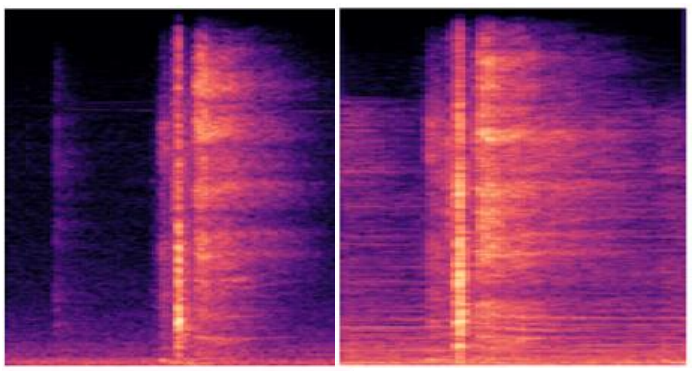

Figure 3. Examples of spectral images derived from reference actuations acoustics profiles – without (left) and with (right) background sound.

Results

After building the model on the test/validation data set, and while using data both with and without background sound, predictions of the test set were done. Overall, the results are very inspiring since the accuracy (fraction of correct classifications) is approaching 90%, even with a mixture of relatively silent background profiles and noisy traces. It is also noted that the approach is very sensitive to small differences, such as the different orifice sizes.

The results are shown in the confusion matrix displayed in Figure 4. Ideally, all data points should fall on a diagonal line from top left to bottom right, whereas points outside this line are misclassifications. Most misclassifications occur between the 62 µL class and reference samples, or between the two classes with different orifice sizes.

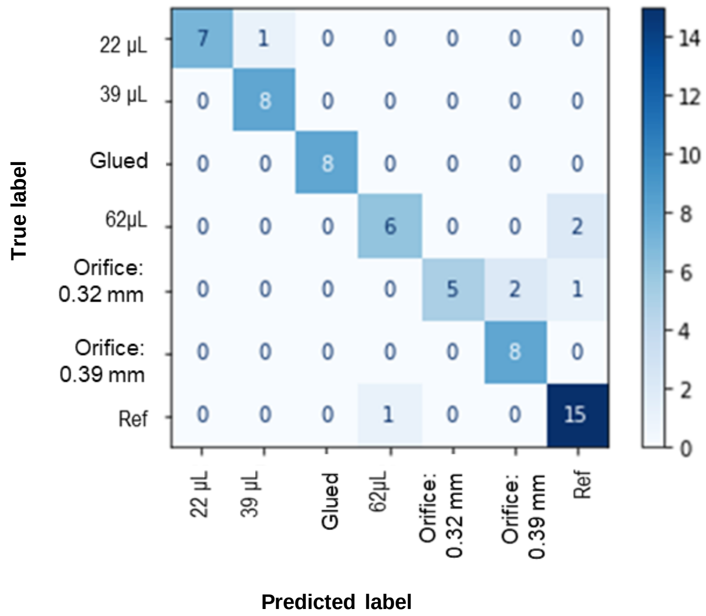

Figure 4. Confusion matrix showing the different classes in the data set. True label is the true class and predicted label is the class predicted by the model. Labels as outlined in the Experimental section.

Conclusions

- The results confirm that AE profiles combined with machine learning algorithms is powerful in terms of extracting relevant data from complex acoustic profiles.
- The method has the potential to be used for adherence monitoring in domestic environment.

References

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2. L. Karlsson, M. Josefson. P. Andersson, S. Folestad, Acoustic Emission Characterization of Inhaler Performance, Inhalation Magazine. August (2016) 26-28.
3. E. Nilsson, M. Josefson, L. Holmstén, P. Andersson, L. Grandinarsky, M. Ferriter, L. Karlsson, SoundCatcher: Acoustic Emission with Machine Learning for Monitoring of MDI Adherence and Detection of Non-optimal Actuation Performance, DDL2022, Abstract, Accepted

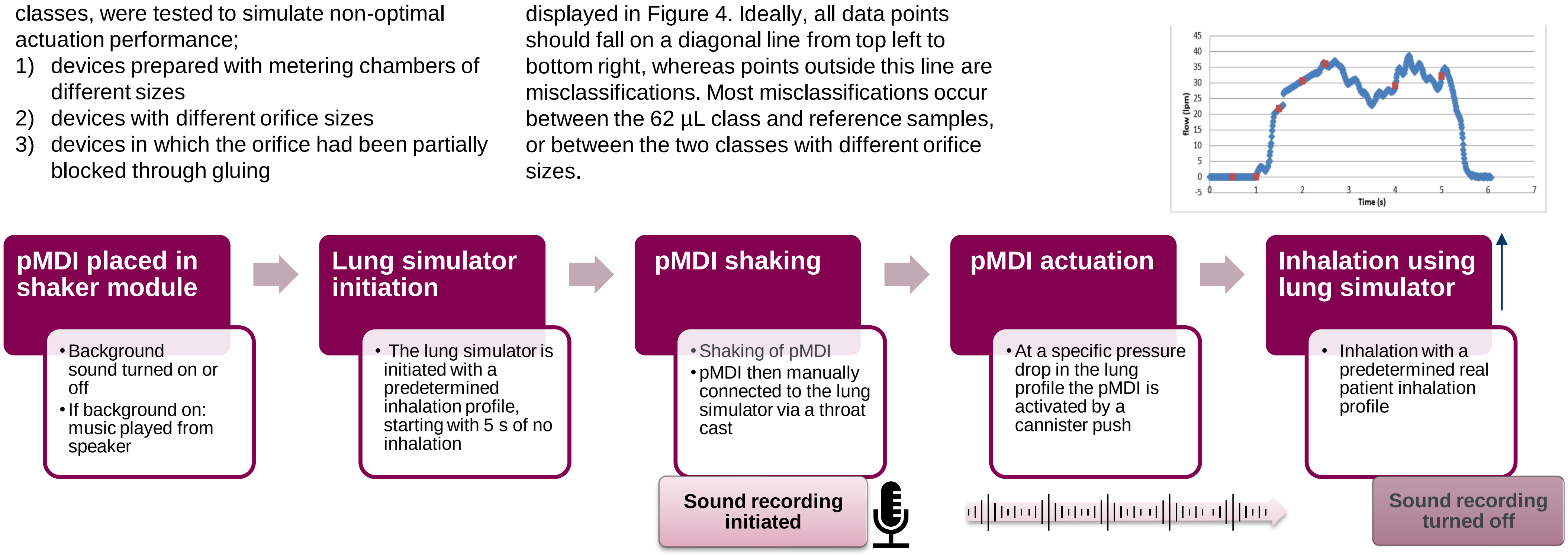

Figure 1. Flowchart of the process for identification of non-optimal or unexpected actuation performance in a domestic-like environment.