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Initial Assumptions for the System of Automatic Detection and Classification of Aircraft Noise Events

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Abstract The present study undertakes the development and implementation of an algorithm for an automatic separation of acoustic events related to aircraft flights. The data are provided by noise monitoring stations operating as part of multi-point continuous noise measurement systems around small and medium-sized airports and helicopter landing sites in Poland. The article presents initial assumptions of the developed method based on the conclusions of the research. For this purpose, two different methods of airborne noise signal detection will be discussed. The first method is based on the analysis of the value of the changing rate of the signal being the difference between the value of the analysed sample and the value of the *h-th* previous sample of the recorded sound level time history. The second method uses a convolutional neural network operating on values recorded in 1/3-octave bands. The objective of the study is to examine the effectiveness and limitations of the selected methods on the collected representative input data.

Keywords: aircraft noise, noise monitoring, noise detection.

1. Introduction

Aircraft noise is the most health-threatening source of noise pollution among all modes of transport [1-3]. The literature has documented the direct and indirect impact of noise on health, involving both auditory and non-auditory sensations [4]. First of all, noise generated by various means of transport, such as air, road and rail traffic, have various negative effects on people [5, 6]. Snellen et al. [7] attributed the variability of noise generated by different aircraft to aircraft characteristics such as engine, speed or changing weather conditions. In order to counteract aircraft noise, various measures have been undertaken to reduce it [8]. Firstly, airplanes are less noisy [9], and secondly, procedures and airport operations have been introduced, which should result in the reduction of noise generated by airplanes in populated areas [10]. Many models of noise monitoring are viewed as approximations of such models, which, in fact, infers deviations from the predictions of the model from actual noise levels [11]. Such approximations can include an airplane model as a point source [12], or the assumption of predefined variability of engine thrust settings along the flight [7]. Therefore, it is very important to compare the model values with the measured ones and to assess their compliance quantitatively. Thus, the paper presents initial assumptions of the method being developed of automatic separation of acoustic events related to aircraft flights.

2. Methodology

To assess the effectiveness of possible approaches to the identification of aircraft noise events, two detection methods were selected, based on different principles. While the former method uses multi-threshold triggering of A-level processed time history [13], the latter uses multi-stage processing. First, the events are detected based on a simple detection threshold and then they are processed by a convolutional neural network [14].

To ensure that the efficiency assessment is reliable, analyses with the use of both methods were carried out based on the same set of input data. The noise was recorded for a month at a measurement point located 3 km from the runway threshold, within the acoustic impact range of two take-off routes and one approach route (see Fig. 1). The main sources of background noise were two roads, one of which has a traffic volume exceeding 3,000,000 vehicles per year. The location of the measuring point was selected to take into account the influence of the acoustic background having high variability level.

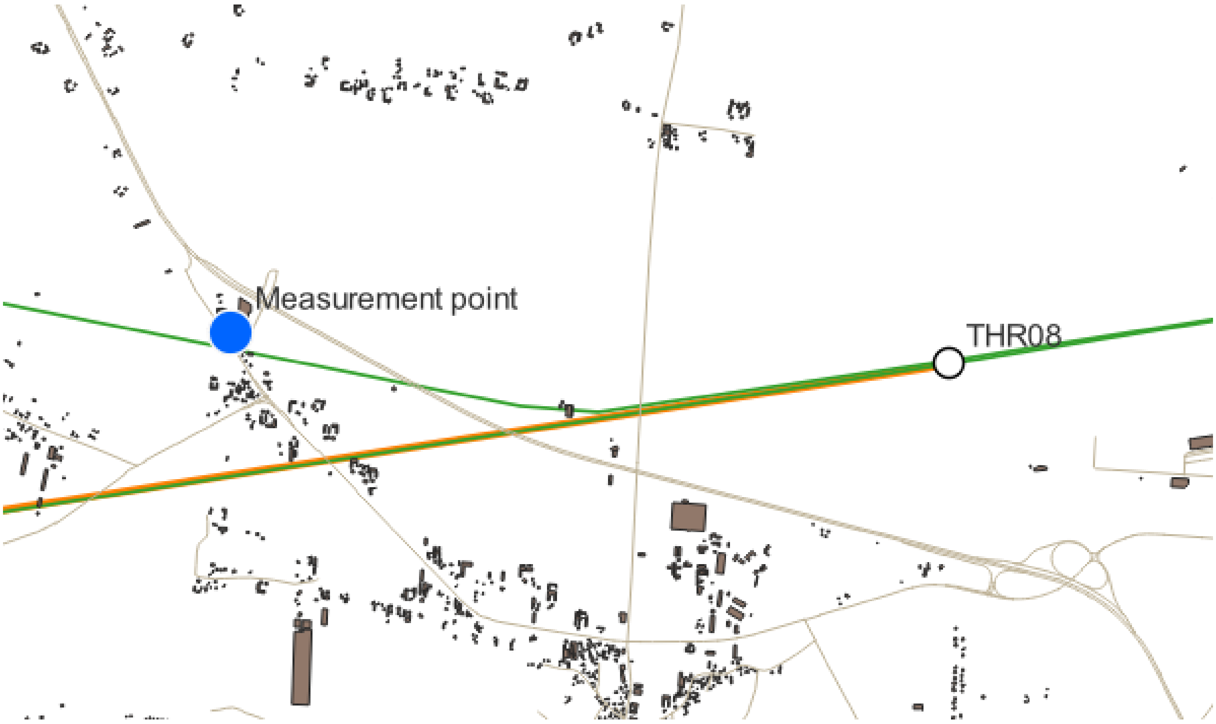

Figure 1. Location of characteristic points and course of routes: approach (orange), take-off (green).

The measurement results (A-weighted sound pressure level and 1/3 octave band levels, recorded with 500 ms step) were manually correlated with non-acoustic data: flight records and aircraft trajectories. The acoustic events detected and labelled this way served as a reference for the results obtained by the analysed methods.

2.1. Multiple-threshold method

Knowing that we measure the changing rate of the function value as the quotient of the function value increment to the length of the interval in which the increase took place, we can estimate the variability of the acoustic signal (A-weighted acoustic pressure level) over time. The proposed methods use the changing rate between the current value $a(t)$ and the *h-th* previous sample, $a(t\text{-}h)$ according to the following equation:

$$V_a = \frac{a(t)-a(t-h)}{h}, \tag{1}$$

where $a(t)$ is the recorded sound pressure level.

The obtained waveform is smoothed using the IIR filter:

$$y_n = \alpha x_{n-1} + (1-\alpha)y_{n-1}, \tag{2}$$

where α stands for a smoothness coefficient between 0 (0%) and 1 (100%), x_n is the input sample and y_n is the filtered sample. The filtered values are analysed using the set of thresholds T_h, T_{L1}, T_{L2}. Exceedance of T_h value detects the beginning of the rising slope, indicating the beginning of the noise event. T_{L1} corresponds to the falling slope and triggers detection of T_{L2} threshold. Exceeding the T_{L2} value ends the event.

The method assumes that appropriate thresholds allow the detection and classification of an aircraft noise event. The filter defined in this way introduced time delay, which had to be compensated to obtain accurate event boundaries. An example of the detected event is shown in Fig. 2. The detection thresholds were iteratively adjusted to maximize detection efficiency because of different input data characteristics: difference in time history resolution and measurement point location resulting in different event shape.

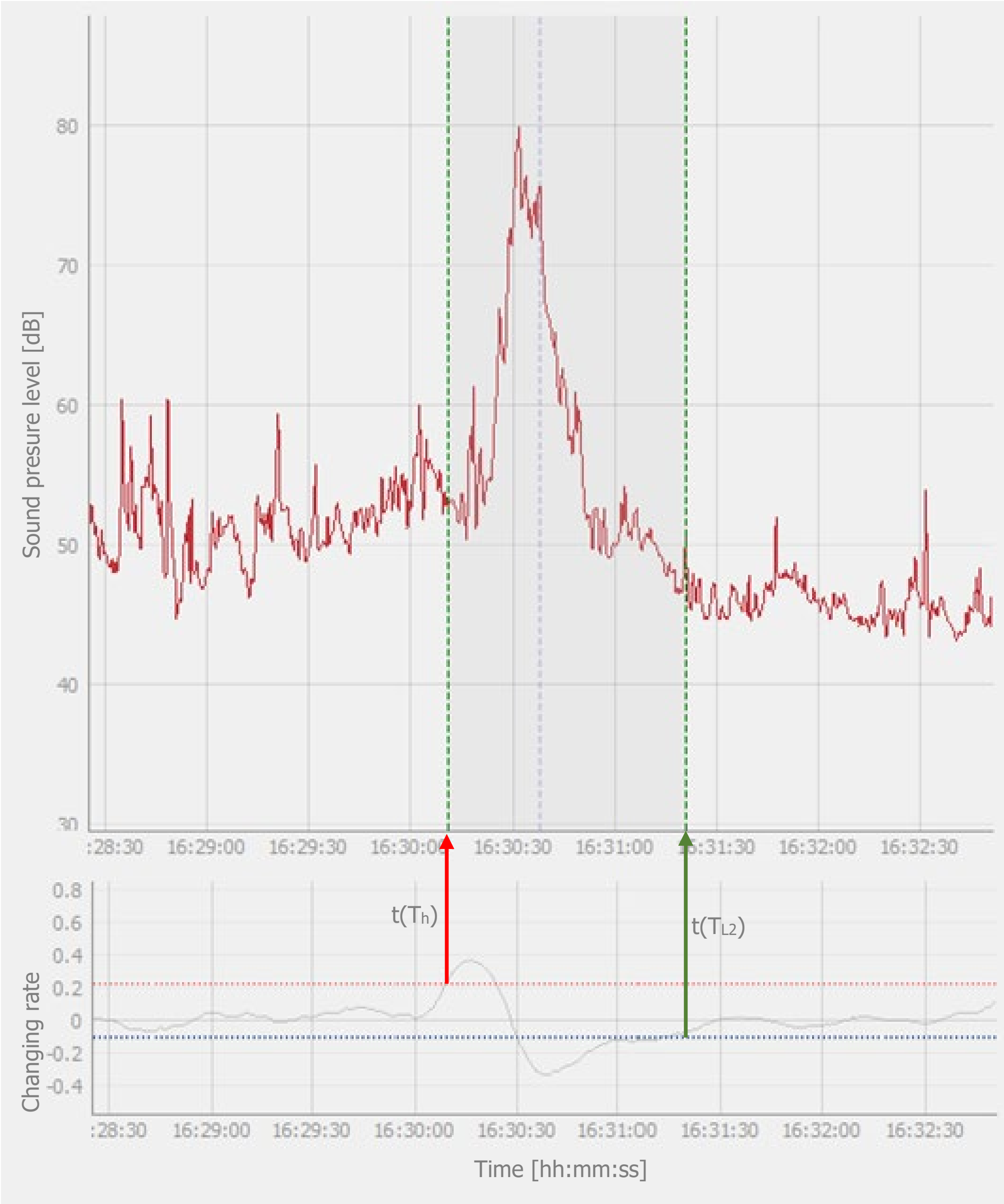

Figure 2. Detected event (top) along with filtered finite difference (bottom) and thresholds: T_h (red), T_{L1} (blue), T_{L2} (green).

2.2. Convolutional Neural Network method

The first stage of processing is the detection of noise events fulfilling loose criteria: sound pressure exceeds 65 dBA and is maintained at 63 dBA or higher for at least 8 seconds. Due to a difference in the location of noise monitoring station in relation to the take-off and approach routes, resulting in an insufficient number of detected events, the initial criteria were altered to 60 dBA and 58 dBA, respectively. The collected events were pre-processed to standardize the dimensions of the input to the neural network.

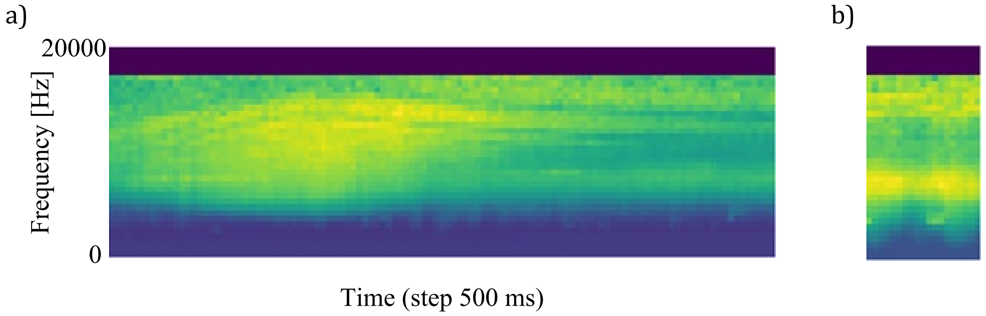

Figure 3. Sample spectrograms: a) aircraft event, b) non-aircraft event.

The classification of the events was performed by the convolutional neural network (CNN), implemented in TensorFlow. The complete implementation and sample data are available at https://github.com/neheller/aircraftnoise. The network design is based on LeNet-5 [15] architecture enhanced with batch normalization [16] and dropout regularization [17] techniques.

Originally, the network was trained on approximately 900 events whereof majority was labelled as aircraft noise. In our approach, a larger set of around 2000 events was used. To mitigate the bias [18], the training samples were evenly distributed: exactly half of them were labelled as aircraft events and the other half as non-aircraft ones. Contrary to the original approach, we used data from one measurement point, expecting improved classification.

3. Results and analysis

The detailed analysis shows that the approach presented in the multiple-threshold method allows for more precise acoustic events extraction in time domain (Fig. 4). Sound exposure level (SEL) calculated for the presented example is by 0.4 dB higher for the multi-threshold method. However, such performance requires favourable acoustic conditions: low and stable background noise level, similar source characteristics (route, operation type, aircraft type).

Table 1 shows the event detection performance for the selected threshold values. The first presented set displayed the highest accuracy (the lowest number of false-positives and the highest number of true-positives) and it was used in further analysis.

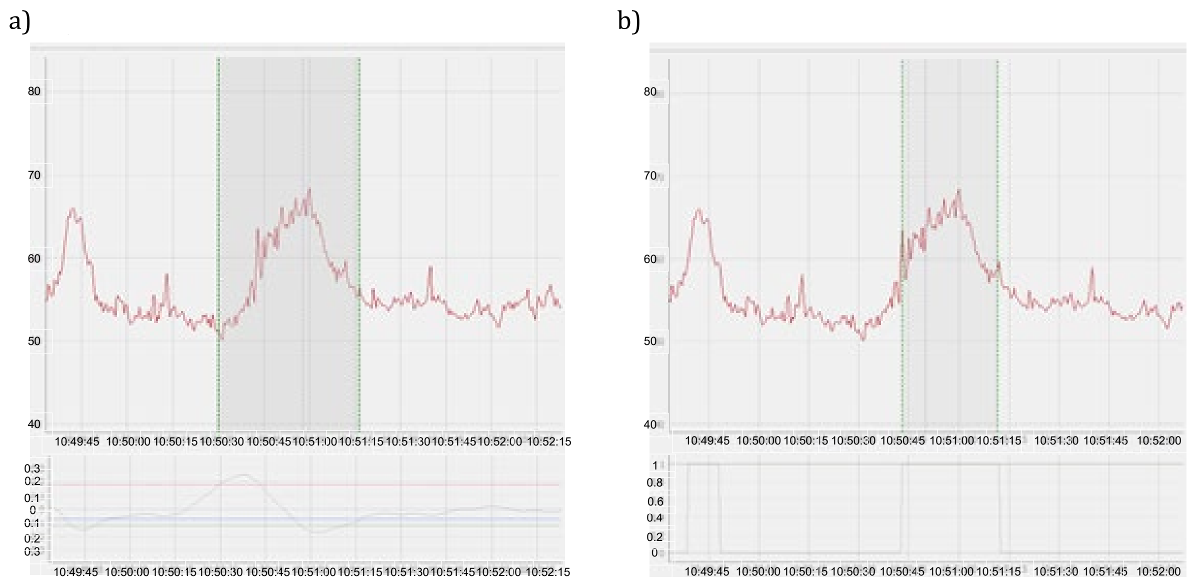

Figure 4. Extracted events using: a) multi-threshold method, b) single threshold method (first stage of CNN method).

Table 1. Analysed threshold sets.

T_h	T_{L1}	T_{L2}	Total events detected	Incorrect events (false positive)
0.25	**-0.19**	**-0.13**	**1052**	**368**
0.22	-0.16	-0.11	1810	952
0.25	-0.17	-0.13	1148	438
0.24	-0.18	-0.10	1236	492
0.23	-0.20	-0.09	1209	463

The method is sensitive to changes in the noise event envelope, which can be caused by a varying aircraft operation type (change from approach to take-off) as well as by the change of aircraft route. The performance can be potentially improved by changing the thresholds with each change of operating conditions. Such an approach is often not possible in continuous unattended aircraft noise monitoring.

In this method, event extraction is equivalent to classification. Out of 1138 manually correlated events, 60% were correctly identified using the analysed algorithm, which is significantly less than the reported 93% [13]. 32% of the events were identified incorrectly (false positive).

During the extraction stage of the CNN method with the adopted threshold values, 4829 events were detected. The excess events were randomly removed for network training purposes. At that stage, 1110 out of 1138 manually correlated events were extracted.

The network performance was evaluated using 10-fold cross validation, and it was trained 5 times with random weight initializations for each fold. The validation results are presented in Fig. 5.

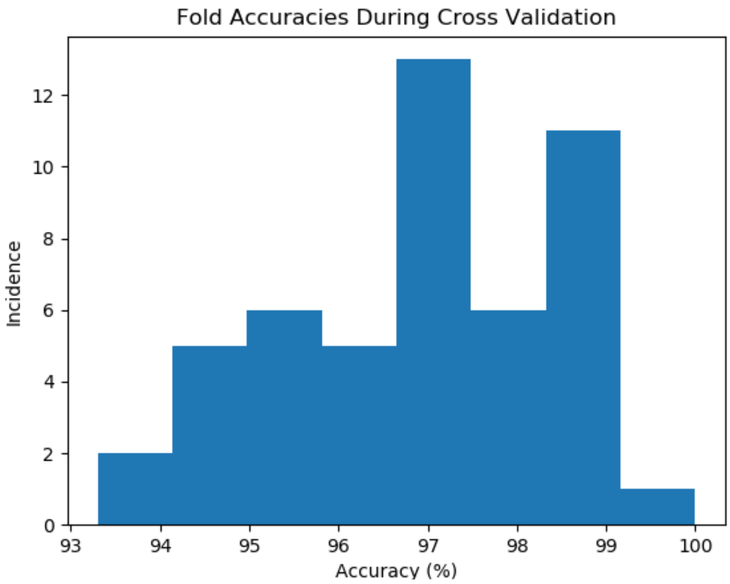

Figure 5. Final classification accuracy.

The classification performance obtained during the validation reached 97%, which is consistent with the original results. The final effectiveness of the method was determined taking into account the correction for the number of detected events. 95% of the events were correctly identified. The false positive rate was 10%.

4. Future work

Both analysed methods turned out to be most vulnerable at the event extraction stage. Either the number of extracted events was insufficient, or the events time boundaries were calculated inaccurately. The discussed methods did not allow for the detection of low-level events, which should ideally be detected in autonomous aircraft noise monitoring system, allowing for precise long term noise levels calculation. One of possible solutions for these problems involves combining both presented extraction methods. Another one, which seems to be the most appealing, moves the extraction stage to the end of the processing, using continuous measurement results as the input data for the neural network, creating continuous aircraft noise similarity classifier [20].

Most research in the aircraft noise detection field focuses on analysing data from a single measurement point, while most monitoring systems consist of multiple points, located in a certain relation to flight paths. This additional piece of information can be used for the improvement of aircraft signal detection, even in acoustically challenging environments in areas which should often be subjected to airborne noise measurements. The foreseen direction of further work is the use of the combination of convolutional neural network (CNN) with long-short term memory (LSTM) network architecture [21], capable of capturing temporal relations between the analyzed data.

5. Conclusions

The performed analysis (Table 2) showed that both methods fulfil the requirements of the ISO 20906:2009 standard [19] (over 50% of successfully detected aircrafts and less than 50% of false events). The results of the CNN method confirmed by those presented in the original paper [14] seem much more promising, paving a way for the detection method that will be used in the emerging monitoring system. The CNN method is definitely more effective than the method based on multiple thresholds.

Table 2. Final performance.

Method	Identified events	Incorrect events (false positive)
Multi-threshold method	60%	32%
Convolutional neural network method	**95%**	**10%**

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Additional information

The authors declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits have been obtained.

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