CLASSIFICATION OF ENVIRONMENTAL NOISE BY MEANS OF NEURAL NETWORKS.

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ABSTRACT
This paper presents a monitoring system which classifies noise by means of neural networks. The system is based on two microphones, and four networks working in parallel; each classifying one type of aircraft. The classification units are developed from measurements at different airports and roads. The input parameters are all derived from 1/3 octave band levels, calculated every 1/8 second. The networks have been tested against real events like take-off, landing, road traffic and farm-machinery.

INTRODUCTION

In spite of the advances that have been made in measuring, modelling and optimising aircraft operations, the noise caused by air traffic is still a severe problem to many people. In order to reduce the annoyance, the Norwegian authorities have imposed a noise limit for the dose acceptable <u>inside</u> a dwelling, a dose where only aircraft noise is to be contributing. This decision involves two consequences:

1: A monitoring system which measure, classify and calculate the noise must be available, and

2: Mitigating actions have to be taken if the dose reach the limit.

The first task is not trivial because of the need for classification. To our knowledge, an instrument which perform all the three tasks directly is not commercially available. The measurements will be performed outside the house of the complainer, for a week or two, and the quantity which is to be calculated is the Norwegian index EFN, which is quite similar to the L_{DEN}, a time-of-day weighted equivalent level.

In order to classify the dose correctly, the system must be able to discriminate the different sources, either by directional methods (two or more microphones), acoustic means, or a combination of the two.

THE CLASSIFICATION PROBLEM.

In cooperation with Norsonic and Luftfartsverket (Norwegian Air Traffic and Airport Management), SINTEF Telecom and Informatics evaluated different ways to separate the noise sources. Because of the high cost of microphones that meet the relevant ISO standard for outdoor measurements, directional methods alone was excluded (an array of microphones). By utilizing the nature of the sound itself by extracting spectral information, an Artificial Neural Network (ANN) was thougth to be the best candidate.

Aircrafts are divided into four categories: 1)jetplanes, 2)helicopters, 3)piston engines and 4)turboprops. In order to separate aircraft noise from all other noise, and distinguish the four categories from each other, there must be some difference in the sound itself , in the spectra and signatures of the signals; both between aircrafts and other sources, but also between the different types of aircrafts. The main challenge when working with a Neural Network is to find input parameters to the network which exploit these differences. In our case the parameters was defined by studying typical spectra and signatures (from different airplanes). Special bands of interest was averaged in time and frequency, building up a set of distinct input parameters. Also single spectral components was evaluated. Figure 1A and 1B show typical spectra from the four different types; we see very clear spectral components for both helicopter and piston engines, while the spectrum from the jetplane is broad and smooth, ranging from 20 Hz to 6-7 kHz.

The performance of the network is very sensitive to the composition of the dataset used for training, as the data must reflect the total range in both time and frequency domain in order to generalize well. This is a big challenge in aircraft noise classification because of the large dynamic range in both intensity, duration and spectrum of the same source. One example is a jetplane passing directly over the head of the observer. This event will last for some seconds with a level of up to 105 dBA, while a plane passing at some distance away may last for a minute or two, never higher than 55 dBA.

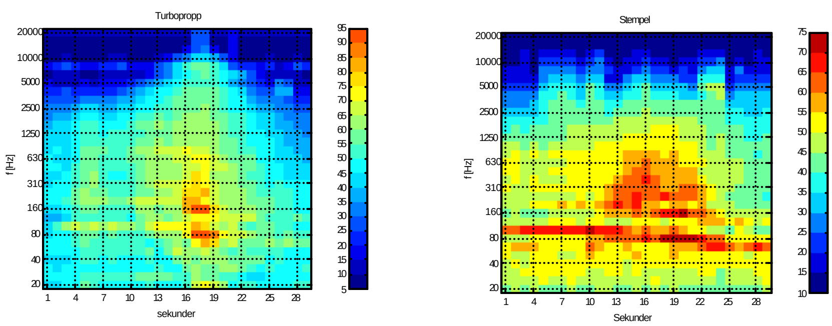

Figure 1A Spectra as a function of time for a turbo prop (left), and a piston engine (right). Resolution along the y-axis is 1/3 octave band, with the center frequency as the label. The level in dB is given by the colour.

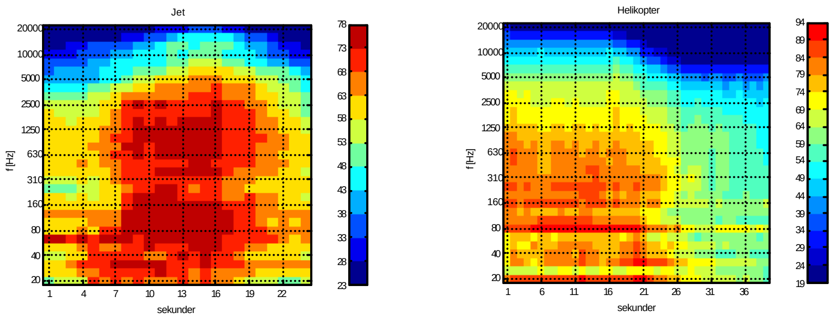

Figure 1B Spectra as a function of time for a jetplane (left) and a helicopter (right). Resolution along the y-axis is 1/3 octave band, with the center frequency as the label. The level in dB is given by the colour.

Another difficulty is the combination of sources, mainly cars and aircrafts, which might often occur if the system is to be placed close to a road. The problem is not only how to make a correct classification, but also how to do the calculation. What is the contribution to the dose if the sources are relatively equivalent, can we ever neglect the whole event?
If the network cannot deal with these problems, one may remove the weak categories. This will minimise the error in the dose-calculations.

SYSTEM DESCRIPTION

The Neural Network is implemented as a part of the software of an otherwise normal noise monitoring system, consisting of two units. One unit is performing the measurements, and is designed to be placed anywhere; with internal power-supply, and with a high mast for the sensors. This autonomous part consists of a Norsonic 121, a PC, a mobile phone line (GSM) and a classification module based on Neural Networks.

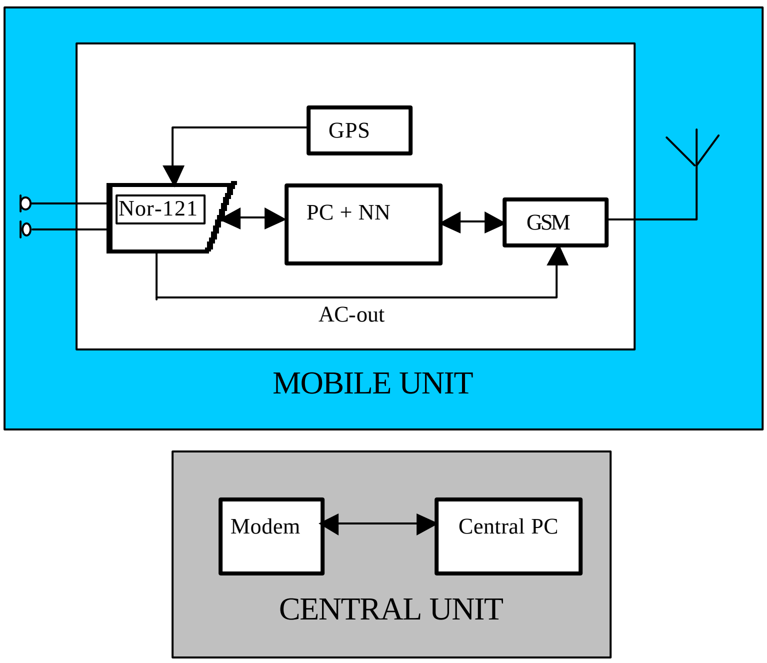

Figure 2 Complete monitoring system.

A second microphone is also available with elevation information, if needed. This might be helpful in complicated cases. The other half of the system, the central unit, is the stationary part with the user interface. The calculations of the dose is performed in this part . There is a possibility for the user to listen to special tracks of interest, and compare them to the classification result. A sketch of the system is shown in Figure 2.

In addition to the calculation of EFN, the system is also designed for being able to count the number of events caused by different propulsion systems. The propulsion systems are divided into four categories; turbofan, turboprop, piston engines and helicopters. This however, is subsidiary.

BUILDING AND TRAINING THE NETWORK.

<u>Measurements</u>

A total of approximately 600 different sequences have been measured at Norwegian airports, in order to get a wide representation of different aircrafts, different distances to the sources, different ground conditions and different weather conditions, all of which will influence the character of the sound. Trains, busses, cars, farming machinery, building noise and general noise in cities have also been recorded to feed the network with examples describing the group we do not want to contribute in the calculations. Some of the sequences include many events.

<u>Architecture and Training Philosophy.</u>

The Neural Network is developed using the software "Neuroshell2". We have used a Backpropagation Architecture, because these networks usually generalize well. This is a supervised type of network, e.g. trained with both inputs and outputs. As a learning paradigm we have used a standard three layer connection, where every layer is connected to the immidiately previous layer. The architecture is shown in Figure 3.

The output from neuron j in layer i can be expressed as u^i_j:

$$u^i_j = f(b^i_j + w^i_{j,1}u^{i-1}_1 + w^i_{j,2}u^{i-1}_2 + \cdots\cdots + w^i_{j,N}u^{i-1}_N)$$

where b^i_j is a constant spesific for this neuron, $w^j_{j,n}$ is a weightfactor to which the output from neuron n in layer i-1 is multiplied. The function f is usually an unlinear function, which maps the sum to the range [-1 ,1] or [0,1].

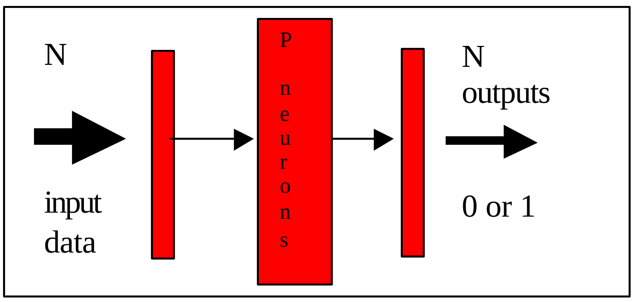

Figure 3. Network architecture.

As a part of the training methodology approximately 20 % of the training set is used for testing the network during training. The vectors are chosen randomly, and is only used for this test. The network is applied to the test set every 200 input-pattern, and the mean square error is computed. Whenever the mean square error is less than the previous, the network is saved. The network stops training when there is more than 200 000 patterns since last updating.

Different Nets

To reflect quick changes in the time signature, a new input pattern is fed to the network every 1/8 second. As stated, the input vector consists of averaged values in time and frequency, based on 1/3 octave band values. Some signal prossessing has also been done to emphasize the strong spectral components for some sources. 18 different nets have been tested for each of the four sources, varying time-averaging, input parameters (maximum 26), detection level, scaling of input parameters, number of nodes in hidden layer,and how to define the fasit.

Postprossessing

The binary output from the net will tend to oscillate for a short time now and then, and this is filtered away in a postprossessing unit. Because there are four net running in parallel, the output from the four should also be correlated, never allowing double classification. The last stage is the calculation of the dose, which is based on a local maximum (A-weighted,slow) within the relevant time interval (when the output from the NN is high). This is the final requirement for accepting the detected event as a real aircraft event.

RESULTS AND DISCUSSION

The networks have been tested twice, the first time with datasets from the same positions (same position but different datasets) as used for training, the last test with datasets from total new positions.

With datasets from the same position included in the dataset for training of the system, the performance was very good; - for piston engines, jetplanes and turbo-props, all events were detected and classified correctly, for helicopters 87.5 %. At the same time less than 0.5 % false alarms existed. This performance was achieved with a relatively high detection level, and 26 input parameters. The test-sets consisted of all four aircraft types, cars, busses, tractors, trains, and other more constant-noise sequences. There was no sequence with two sources of equal strength, and there was no sequence with taxing / reversing.

When using datasets recorded under different conditions, the performance was reduced. The testset now included both taxing and reversing, but lacked helicopters due no traffic at the spesific airport used (Værnes). Sequences with aircraft-events in a high background noise were present, also recordings with snow on the ground (all datasets used for training were recorded in summer / autumn). The best result from this test is presented in Table 1.

NETWORK	Correct detection [%]	False alarms [%]
TURBO-PROP	76	0.02
PISTON ENGINE	66	0.02
JET-PLANES	90	30

Table 1. Results from Test 2.

The results show that the system can still be improved, especially the jet-classificator. By decreasing the detection level, the number of correct detections will increase, but so will the number of false alarms. By increasing the detection level the opposite will happen. The many false alarms in jet-classification were due to passing of cars in a relative high background noise. To the ear the noise from the tyres sounded like a jetplane at some distance. Since the last stage in the post-prossessing unit was not implemented, and neither the extra microphone, it is too early to state what is the best, higher classification prosent with a higher number of false alarms, or reduced classification prosent with less false alarms.

The turbo-prop was the best net alltogtehter, with very few false alarms, and a relative high detection score. By decreasing the time the output had to stay high before accepting it as an event, many of the missing events for both turbo and piston would have been detected, but this would also lead to an increase in false alarms. Because we have not studied the consquence this will give to the dose contribution, we cannot conclude what is the best.

The results did not include all the post-prossessing units. The output from the networks were filtered, but not correlated to each others completely, and not related to a local maximum (A-weighted, slow). Especially a number of the false alarms for jetplanes will be reduced with this part present.
The results show that it is an advantage if the system is trained in the posistion where it is meant to measure. This will increase the performence, and also the database for training sets.

CONCLUSION

A final evaluation of the complete system is not possible before all the post prossessing units are implemented. We believe though that such a system has great potensials in monitoring and calculation of aircraft noise.