Environmental Noise Monitoring. 1st. Stage: Aircrafts Noise Patterns Recognition

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Abstract. The noise level in a city has fluctuations between 50 dB (A) and 100 dB (A). It depends on the population density and its activity, commerce and services in the public thoroughfare, terrestrial and aerial urban traffic, of the typical activities of labor facilities and used machinery, which give varied conditions that must be faced of diverse ways within the corresponding normalization. The sounds or noises that exceed the permissible limits, whichever the activities or causes that originate them, are considered events susceptible to degrade the environment and the health. This paper is a task within an environmental noise monitoring system and it presents the analysis of the aircraft noise signals and a method to identify them. The method uses processed spectral patterns and a neuronal network feed-forward, programmed by means of virtual instruments.

1 Introduction

Much of this work involves the collection and analysis of large amounts of aircraft noise data from the Noise and Track Keeping systems (NTK) installed at airports. Like any other measured quantity, aircraft noise measurements are subject to some uncertainty, which can influence the quality of the final measured result [1].

The uncertainty contributions for a typical noise study can be considered in two groups. The first group includes the components of uncertainty associated with the measurement of aircraft noise at a particular monitoring location. The second group includes the components of uncertainty associated with any subsequent data analysis that may be carried out [1], [2], [3]. The overall accuracy of any type of measurement is limited by various sources of error or uncertainty. Components of uncertainty can essentially be classified as either *random* or *systematic* in nature. When making a series of repeated measurements, the effect of the former is to produce randomly different results each time, which are all spread or scattered around an average (mean) value. In contrast, systematic components of uncertainty cause the measurement to be consistently above or below the true value. For example, when measuring the time with a watch that has been set 1 minute slow, there will be a systematic error (or bias)

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in all the measurements. In a well-designed measurement study, the systematic components of uncertainty should generally be smaller than the random components [1], [4]. Possible sources of uncertainty for aircraft noise measurements include not only the noise instrumentation itself, but also variations in the noise source and propagation path, meteorological variations, the local environment at the measurement site, and also any variance due to data sampling - all of these individual uncertainty components can influence the quality of the final measured result [1]. An internationally accepted procedure for combining and expressing measurement uncertainties is given in the ISO Guide to the Expression of Uncertainty in Measurement [5], [6], [7].

The used aircraft noises in this work have been acquired by means of archives of sounds, whose measurements were made fulfilling the norms mentioned previously, with frequencies of sampling of 22050 Hertz, monophonic, during 24 seconds. In general, this interval, is greater than to aircraft takeoff time, or greater to the time in which the produced noise affects the zones near an airport.

For a same aircraft, several archives of sounds were used, taken for different meteorological conditions and microphone orientation. Two types of microphones were used, which can be considered typical for these measurements. In addition, the sounds were reproduced with three different sound cards.

When the environmental noise monitoring system is in operation, norms of measurements and calibration will be elaborated

2 Diagrams and description of typical architecture of an aircraft noise monitoring station [8], [9].

Generally, a noise monitoring complex system detects, identifies and analyses the noise produced by arriving and departing aircrafts. The Fig. 1 presents a typical architecture of aircraft noise monitoring stations

The noise monitoring system (NMS) measures aircraft noise according to defined criteria. The first step of the system is the collection of the detected aircraft noise, the second the attribution of the noise to a specific aircraft movement. To perform the correlation of the aircraft noise, additional information is necessary, which will be described later.

2.1 EMU - Environmental Monitoring Unit

The EMU consists of

- a digital microphone for noise measurement
- a local unit for data backup
- a modem for transmitting data to the central processing system.

2.1.1 Microphone unit

Each unit is mounted at the end of a mast and equipped with a digital microphone, an anti-wind and bird guard and a lightning arrestor. The microphone captures the analogue noise signal and performs the critical conversion of the signal immediately at the microphone head, and transmits the noise data in digital form to the EMU's electronics. The immediate conversion to a digital signal provides a higher immunity to interference. The unit guarantees an omni directional detection of noise with high reception qualities. The 5 local units are synchronized by the central system GPS clock.

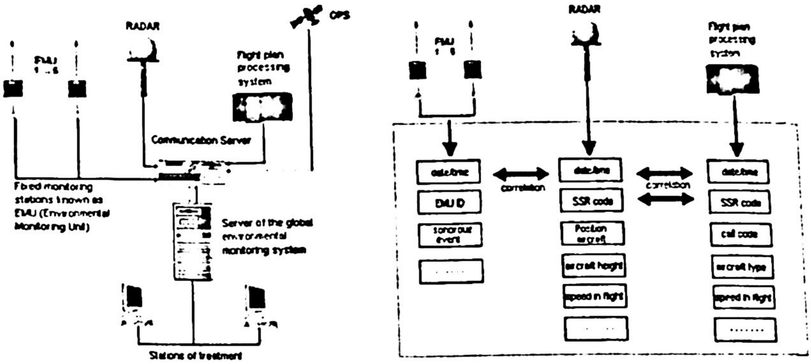

Fig. 1 Typical architecture of aircraft noise monitoring stations and correlation principle

2.2 Central processing system

All the data collected via network or modem from the airport radar, the flight plan processing system and the EMUs are put through to the central processing system which consists of Communication Server and Global Environment Monitoring System. The Communication Server collects:

- the noise events of the five EMUs,
- the radar aircraft tracks,
- the flight plans from FDP (Flight Data Processor),
- the GPS (Global Positioning System) to guarantee the synchronization of the noise monitoring system.

The Global Environment Monitoring System processes and correlates the data acquired by the Communication Server in order to identify an aircraft that produced a noise event. The essential processing in the Global Environment Monitoring System consists of:

- correlating the real time data from the Communication Server server;
- archiving the acquired data, and generating reports about individual events, daily, monthly or annual summaries.

Identification of the noise event: The EMU continuously analyses the incoming noise signal to identify the source of noise. By using various detection algorithms it is possible to identify noise generated by an aircraft flying past, known as event. The process of identifying a noise event is based on threshold and time change criteria. The incoming data are noise events, aircraft flight plans and Radar information. The correlation principle is observed in the right side of Fig 1.

3. Aircrafts noise patterns

The goal of this development stage of the environmental noise monitoring system is to make aircrafts noise signals analysis, that allows to create a method of aircraft noise patterns recognition, that will do possible to identify types of aircrafts. These types of aircrafts can be of helix, turbojet and reaction. On the other hand, it is possible to classify the aircrafts as long reach (high power), medium reach (medium power) and short reach (low power). Committees of Aerial transport and environmental propose an aircraft classification based on the level of noise emission.

The proposed common classification of aircraft is based on the principle that the aircraft operator should pay a fair price that should be proportional to its noise impact, independently of the weight of the aircraft or of the transport service rendered. Such data would make it possible to recognize the environmental merits of larger aircraft, even if these aircraft are noisier in absolute terms when compared to smaller aircraft. Therefore the proposal contains a discretionary provision for additional information to be given to the public concerning the noise productivity of heavier aircraft. This is to ensure that the concept of noise productivity is well understood [10]. The presented method recognizes specific aircraft type.

3.1 Aircraft noise signals analysis

As example, we will present noise signals of some aircrafts. The used aircraft noises in this work have been acquired by means of archives of sounds, whose measurements were made fulfilling the norms mentioned previously, with frequencies of sampling of 22050 Hertz initially, and later to 11025 Hz, monophonic, during 24 seconds. En general, this interval, is greater than to aircraft takeoff time, or greater to the time in which the produced noise affects the zones near an airport (Fig. 2 and 3).

For all used aircraft noises the typical form of the amplitude spectrum is observed from 0 to 5000 Hertz, for this reason, we used a sampling frequency of 11025 Hz, in order to reduce the number of taken samples in 24 seconds (264600 samples). The amplitude spectrum has 132300 harmonics, with $\Delta f = 0.04167$ Hz.

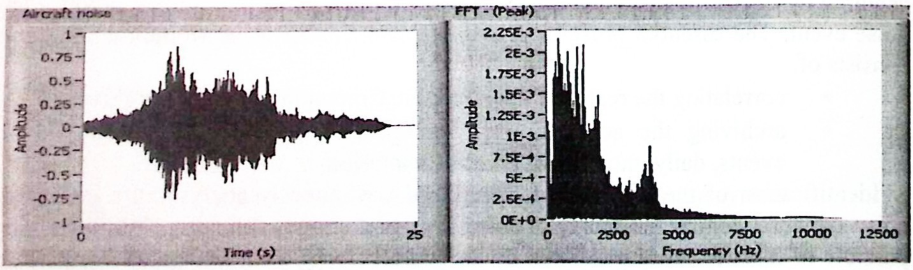

Fig. 2 Noise of Falcon aircraft taking off, with sampling frequency of 22050 Hz.

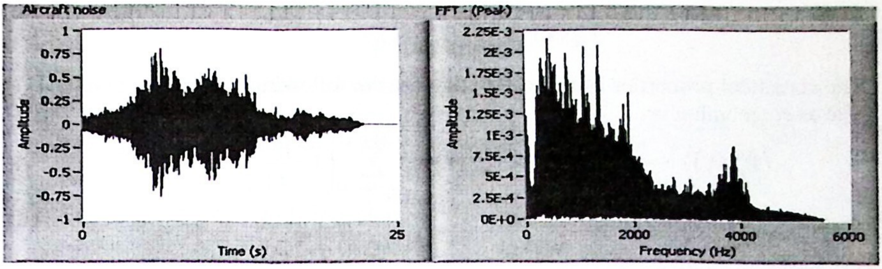

Fig. 3 Noise of Falcon aircraft taking off, with sampling frequency of 11025 Hz.

3.1.1 Reduction of the spectral resolution

It is necessary to reduce the spectral resolution because of the following reasons:

1. The amplitude spectrum has 132300 harmonics and its processing will be very complex.
2. It is only of interest the spectral form.

The following hypotheses are presented:

1. Any reduction method of spectral resolution introduces a tolerance in the initial and final times within the measurement interval of aircraft noise.
   For example, a feedforward neural network is trained with one noise pattern which was acquired from zero seconds from the aircraft takeoff until 24 seconds later. In run time, the aircraft takeoff noise is acquired from 5 seconds until 24 seconds. This time displacement of 5 seconds affects little the spectral form if its spectral resolution has been reduced
2. A median filter (moving average filter) creates a typical form of the aircrafts takeoff noises spectrums.
3. The decimation of average spectrum, with a rate X, conserves the spectral form of aircrafts takeoff noises.

3.1.2 Spectral estimation

In the present work is used the Bartlett-Welch method [11] for spectral estimation. The Bartlett method consists on dividing the received data sequence into a number K, of non-overlapping segments and averaging the calculated Fast Fourier Transform.

It consists of three steps [12]:

1. The sequence of N points is subdivided in K non overlapping segments, where each segment has length M.

$$x_i(n) = x_i(n + iM),\ i = 0,1,...,K-1,\ n = 0,1,...,M-1 \tag{1}$$

2. For each segment, periodogram is calculated

$$\hat{P}_{xx}(f) = \frac{1}{M}\left|\sum_{n=0}^{M-1} x_i(n)e^{-j2\pi fn}\right|^2,\ i = 0,1,...,K-1 \tag{2}$$

3. The periodograms are averaged for the K segments and the estimation of the Bartlett spectral power can be obtained (in this work, we don't use the spectral power) as:

$$\hat{P}_{xx}^{B}(f)=\frac{1}{K}\left|\sum_{i=0}^{K-1}\hat{P}_{xx}^{(i)}(f)\right|^{2} \tag{3}$$

The statistical properties of this estimation are the following ones:

The average value is:

$$\left\langle \hat{P}_{xx}^{B}(f)\right\rangle=\frac{1}{K}\sum_{i=0}^{K-1}\overline{\hat{P}_{xx}^{(i)}(f)}=\overline{\hat{P}_{xx}^{(i)}(f)}=\sum_{m=-(M-1)}^{M-1}\left(1-\frac{|m|}{M}\right)r_{xx}(m)e^{-j2\pi fm}$$
$$=\frac{1}{M}\int_{-1/2}^{1/2}P_{xx}(\alpha)\left(\frac{\operatorname{sen}\pi(f-\alpha)M}{\operatorname{sen}\pi(f-\alpha)}\right)^{2}d\alpha, \tag{4}$$

donde $\frac{1}{M}\frac{\operatorname{sen}\pi(f-\alpha)}{\operatorname{sen}\pi(f-\alpha)}=W_B(f)$ it is the frequency characteristic of the Bartlett

window: $$w_B(m)=\begin{cases}\left(1-\frac{|m|}{N}\right), & |m|\le M-1\\ 0 & , |m|>M-1\end{cases} \tag{5}$$

The true spectrum is convolutioned with the frequency characteristic of the Bartlett window $w_B(m)$. Reducing the longitude of the data window of N points to M=N/K, it results in a window whose spectral wide has been increased by the factor k. Consequently, ***the frequency resolution has decreased for the factor k,*** in exchange for a variance reduction.

The variance of the Bartlett estimation is:

$$\operatorname{var}\left[\hat{P}_{xx}^{B}(f)\right]=\frac{1}{K^{2}}\sum_{i=0}^{K-1}\operatorname{var}\left[\hat{P}_{xx}^{(i)}(f)\right]=\frac{1}{K}\operatorname{var}\left[\hat{P}_{xx}^{(i)}(f)\right]=\!=\frac{1}{K}P_{xx}^{2}(f)\left[1+\left(\frac{\operatorname{sen}2\pi fM}{M\operatorname{sen}2\pi f}\right)^{2}\right] \tag{6}$$

Welch Method [11], [13], [14]: unlike in the Bartlett method, the different data segments are allowed to overlap and each data segment is windowed.

$$x_i(n)=x(n+iD),\ n=0,1,\ldots,M-1,\ i=0,1,\ldots,L-1 \tag{6}$$

Where iD is the point of beginning of the sequence i-ésima. If D=M, the segments are not overlapped. If D=M/2, the successive segments have 50% of overlapping and the obtained data segments are L=2K.

Another modification proposed by Welch to the Bartlet method consists on using a window for the data segments before calculating the periodogram. The result is the "modified" periodogram:

$$\tilde{P}_{xx}^{(i)}(f)=\frac{1}{MU}\left|\sum_{n=0}^{M-1}x_i(n)w(n)e^{-j2\pi fn}\right|^{2},\quad i=0,1,\ldots,L-1 \tag{7}$$

Where U is a normalization factor for power of the function window and it is selected as:

$$U=\frac{1}{M}\sum_{n=0}^{M-1}w(n) \tag{8}$$

The Welch estimation of spectral power is the average of these modified periodograms:

$$P_{xx}^{W}(f)=\frac{1}{L}\sum_{i=0}^{L-1}\tilde{P}_{xx}^{(i)}(f) \tag{9}$$

The average of the Welch estimation is:

$$\left\langle P_{xx}^{W}(f)\right\rangle=\frac{1}{L}\sum_{i=0}^{L-1}\overline{\tilde{P}_{xx}^{(i)}(f)}=\overline{\tilde{P}_{xx}^{(i)}(f)}=\frac{1}{MU}\int_{-1/2}^{1/2}P_{xx}(a)\,W(f-\alpha)\,d\alpha \tag{10}$$

$$\text{Where } W(f)=\frac{1}{MU}\left(\frac{\operatorname{sen}\pi(f-\alpha)M}{\operatorname{sen}\pi(f-\alpha)}\right)^{2}=\frac{1}{MU}\Im\{w(n)\} \tag{11}$$

The normalization factor assures that: $\int_{-1/2}^{1/2} W(f)\,df=1$

The variance of the Welch estimation is:

$$\operatorname{var}\left[\hat{P}_{xx}^{W}(f)\right]=\frac{1}{L^{2}}\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\left\{\left[\overline{\tilde{P}_{xx}^{(i)}(f)\tilde{P}_{xx}^{(j)}(f)}\right]^{2}-\left[\left\langle\hat{P}_{xx}^{W}(f)\right\rangle\right]^{2}\right\} \tag{12}$$

Why Welch method is introduced?

– Overlapping allows more periodograms to be added, in hope of reduced variance.

– Windowing allows control between resolution and leakage.

The Welch method is hard to analyze, but empirical results show that it can offer lower variance than the Bartlett method, but the difference is not dramatic.

• Suggestion is that 50 % overlapping is used.

In this paper, the data segment of 264600 samples, acquired in 24 seconds, is divided in 24 segments: K=24, with 50% of overlapping, therefore, L=2K=48 overlapped data segments, later is applied the FFT (periodogram) to each segment and they are averaged.

3.2 Examples of aircrafts noise patterns

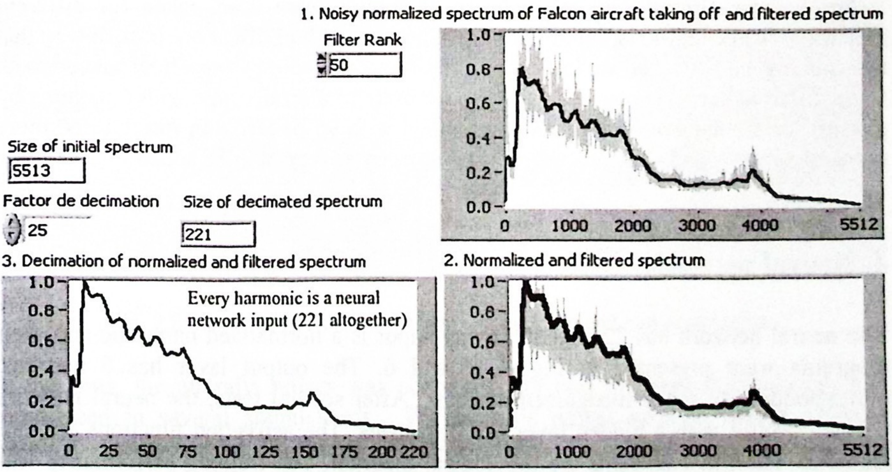

Fig. 4 Example of noise pattern of Falcon aircraft taking off (turbojet)

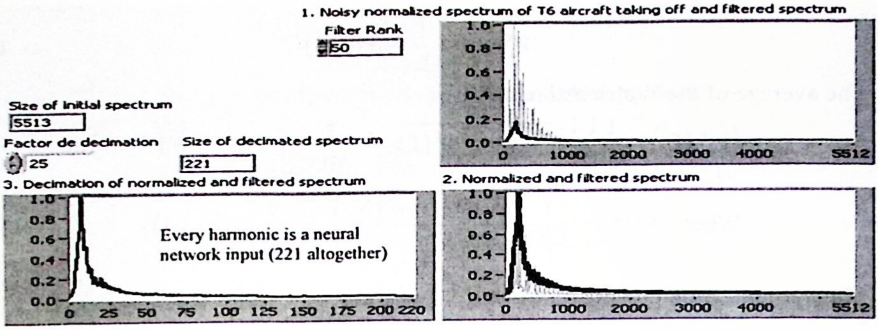

Fig. 5 Example of noise pattern of T6 aircraft taking off (helix)

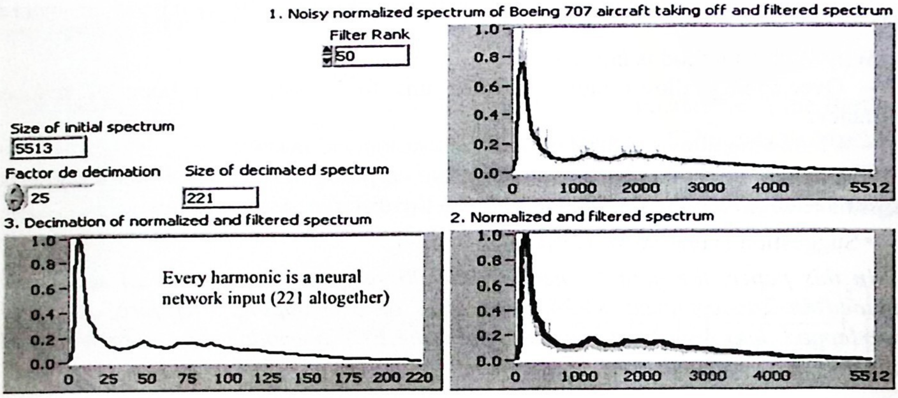

Fig. 6 Example of noise pattern of f Boeing 707 aircraft taking off (helix)

For a same aircraft, several archives of sounds were used, taken for different meteorological conditions, microphone orientation and amplification, in such way that the training patterns had distortions. In addition, the sounds were reproduced with three different sound cards. In this stage, we used 16 aircrafts type with 6 patterns by aircraft. In all, the neural network was trained with 96 patterns. In future tests, more types of aircrafts and greater amount of patterns by aircraft will be added

4. Neural network

The neural network has 221 inputs. Every input is a normalized harmonic and their diagrams were presented in Fig. 4, 5 and 6. The output layer has 8 neurons, corresponding to the 8 recognized aircrafts. After several tests, the neural network was successful with a hidden layer of 10 neurons. The activation functions are tan-sigmoid. The Fig 7 presents the topological diagram. The training performance was successful and it is presented in Fig. 8.

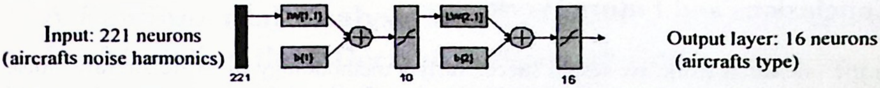

Fig 7. Neural network topological

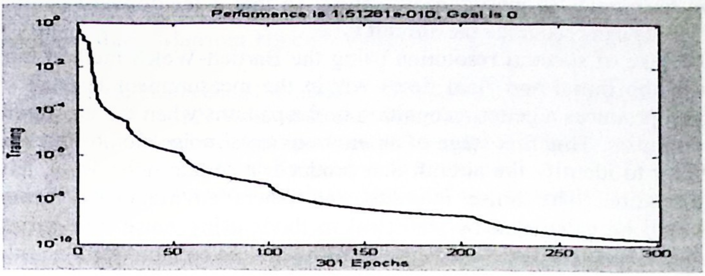

Fig 8. Training performance of neural network

4. Analysis of results

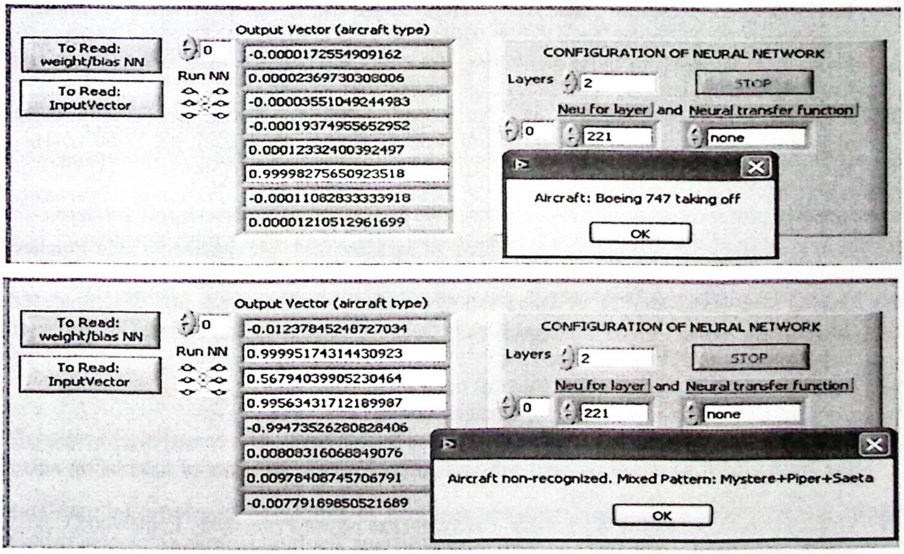

Fig. 9 Example of two tests of patterns recognition and non-recognition

In the tests, the aircrafts noises was acquired with two different microphones and reproduced in several sound cards. For aircrafts noises used in neural network training, the recognition was successful. For a aircraft non-used in the training, the neural network non- recognized a specific aircraft and presented a message with three aircrafts whose mixed noise patterns have similarity to the acquired noise (see Fig. 9).

Conclusions and Future Work

In the presented work, we tested successfully a methodology to create aircrafts noise patterns. It combine the decrease of spectral resolution, a moving average filter and decimation of average spectrum, This method allows reducing the number of significant harmonics in amplitude spectrum, so that a feedforward neural network with 221 inputs can recognize the aircraft type.

The decrease of spectral resolution using the Bartlett-Welch method introduces a tolerance in the initial and final times within the measurement interval of aircraft noise, which produces a better recognition of the patterns when the measurements can have uncertainties. This first stage of an environmental noise monitoring system tests the feasibility to identify the aircraft that produces a certain noise level, having only noise information. The noise intensity and others environmental contamination indicators will be calculated by statistical methods using noise time series. A next goal will be construct a distributed system with wireless communication with Doppler effect compensation.

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