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Development And Testing Of A Mathematical Model Of UAV Acoustic Noise Generation When Training Neural Networks

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***Abstract* — A mathematical model was developed to calculate the frequency composition of acoustic noise of UAVs with horizontal propellers relative to the ground surface and sound pressure levels at these frequencies. The model takes into account attenuation at different frequencies from the distance for the propagation of acoustic waves in the city and outside the city. Using the created model, a dataset of DJI Phantom 3 noise implementations was synthesized, and a convolutional neural model was trained. The results of testing the trained convolutional model proved the operability of the created mathematical model.**

Keywords — unmanned aerial vehicle, mathematical model, noise, frequency components, convolutional neural network, atmosphere.

I. INTRODUCTION (*HEADING 1*)

The current stage of development of unmanned aerial vehicles (UAVs) is characterized by the rapid spread of their use in civil and military areas, in particular in monitoring, logistics, agriculture and reconnaissance operations. In parallel, the need for effective methods of identifying UAVs is growing, as they pose a threat to air traffic safety, military facilities, private territories [1]. Acoustic noise is one of the key information sources for detecting these objects in difficult operating conditions, in particular under conditions of limited visibility or during the operation of electronic countermeasures [2,3].

Modern advances in artificial intelligence open up wide possibilities for detecting and recognizing acoustic noise from UAVs using neural networks. The main problem with using neural networks is preparing large datasets for their training, which is a difficult task because there are so many types of UAVs. The world experience of companies OpenAI, Google, etc. shows that training can be carried out with the addition of synthetic data. Therefore, for machine learning tasks, in particular training neural networks on synthetic data, there is an urgent need to generate large volumes of various acoustic signals corresponding to a wide range of flight parameters and different types of UAVs. However, the process of generating such noise is an extremely complex multifactorial phenomenon, which is due to the interaction of aerodynamic, mechanical and electromagnetic noise sources. The main components of the acoustic signal of a drone are propeller noise (including blade tonal noise and broadband turbulent noise), engine noise (for UAVs with internal combustion engines) or electric motor and gearbox noise (for electric UAVs), as well as the noise of turbulent flow around the structural elements of the fuselage [4]. Each of these components has its own spatiotemporal structure and is influenced by factors such as flight speed, powerplant operating mode, propeller group configuration, and atmospheric conditions.

Traditional approaches to mathematical modeling of UAV acoustic noise are based on fundamental aeroacoustic equations (the Fox-Williams-Hawkings equation, the Kerle analogue for rotating propellers) and empirical correlations [5]. However, these methods require significant computational resources, and their accuracy is significantly reduced when modeling real flight conditions taking into account wind gusts, atmospheric turbulence, and nonlinear effects.

Purely experimental models actually require a large dataset, the processing of which creates such a model [6,7]. Therefore, approaches that combine a mathematical approach with a small number of practical measurement results can be considered practically valuable. The purpose of this article is to develop a mathematical model of UAV acoustic noise generation, optimized for use in training neural networks, and to conduct a comprehensive test of its adequacy by comparing it with experimental data and physically justified analytical solutions.

To achieve the research goal, it was decided to create a mathematical model of the frequency composition of UAV noise, which is related to the design features. The results of practical measurements were used to determine the level of radiation at these frequencies, and the general theory of acoustic wave propagation in the atmosphere was used to determine the level of attenuation of acoustic noise at the corresponding frequencies with distance.

II. Development of a Mathematical Model and Research Algorithm

A. Mathematical model of the spectral composition of UAV noise

According to research [8], the acoustic noise of UAVs has 4 components: rotor, motor, structural, aerodynamic. The fundamental rotor frequency and its harmonics arise from the rotation of the propeller blades. The values of these frequencies are calculated by the formula

, $k=1,2\ldots n_{bl}$ (1)

where n_{bl} is number of propeller blades; *RPM* is engine speed, rpm; *k* is harmonic number. The second component — motor noises arise as a result of electromagnetic noises of BLDC motors, which excite mechanical vibrations of the stator and structural elements of the engine. Mechanical vibrations are radiated into the environment in the form of acoustic waves at electrical switching frequencies and their harmonics, which are determined by the ratio [9]

$$f_{pole} = \frac{n_{пол} \cdot RPM}{60}, \quad (2)$$

where n_{pole} is the number of the electric motor pole pairs.

Between the motor and the propeller, bearings are installed that form harmonics according to ISO 15242

$$f_{BPF} = \frac{N_{balls}}{2} \cdot \frac{RPM}{60} \cdot \left(1 \pm \frac{d_b}{D}\right)$$

$$f_{BSF} = \frac{D}{2d} \cdot \frac{RPM}{60} \cdot \left(1 - \left(\frac{d_b}{D}\right)^2\right)$$

$$f_{BSF} = \frac{RPM}{2 \cdot 60} \cdot \left(1 - \frac{d_b}{D}\right), \quad (3)$$

where *Nballs* is the number of balls in the bearing, *D* is the diameter of the rolling circle, mm; d_b is the diameter of the ball, mm.

The UAV propeller can be considered as a cantilever beam with a concentrated load at the end [10-12]. Then the natural frequency of oscillations of such a system generates structural noise, the frequency of which is calculated by the formula

$$f_{struct} = \frac{1}{2\pi} \sqrt{\frac{k_{struct}}{m_{eff}}}, \quad (4)$$

where k_{struct} is the stiffness of the structural element, N·m/rad; m_{eff} is the reduced mass, kg.

When the propeller blades rotate, a vortex wake is created according to the Strouhal criterion [9] and the frequencies are calculated by the formula

$$f_{aero} = \frac{St \cdot v}{L_c}, \quad (5)$$

where *St* is the Strouhal number (dimensionless coefficient, St≈0.2 for cylindrical elements); *v* is the air flow velocity near the blade tip, m/s; *Lc* is the characteristic linear dimension of the blade profile, m.

The pressure level of motor and rotor noise is calculated based on data [13]

$$L_{motor}(f) = \begin{cases} 55 + 15\log_{10}\left(\frac{f}{1000}\right) & f < 6000 \text{ Гц} \\ 30 & \text{для } f > 6000 \text{ Гц} \end{cases}.$$

(6)

For broadband structural and aerodynamic noise, the frequency response of broadband noise is determined by the formula

$$B(f) = B_0 - 10\log_{10}\left(1 + \left(\frac{f}{f_{cutoff}}\right)^2\right), \quad (7)$$

where f_{cutoff} is the cutoff frequency (for example, 3500Hz for DJI Phantom 3), Hz. The rotor noise directivity diagram should also be taken into account when calculating. For the case of horizontal arrangement of the blades relative to the ground surface according to [14], the diagram has the form

$$D_{BPF}(\theta) = 10\log_{10}\left[\frac{J_B^2(BM\sin\theta)}{1 + (BM\sin\theta)^2}\right], \quad (8)$$

where J_B is he B-order Bessel function; R is the propeller radius, m; Ω is the angular velocity of rotation, rad/s; *c* is the speed of sound, m/s; M=ΩR/c is the Mach number at the tip of the blade.

B. Model of acoustic waves attenuation in the atmosphere

According to the international standards ISO 9613-1 and ISO 9613-2, the total attenuation of sound when propagating in the atmosphere consists of three independent mechanisms:

$$A_{total} = A_{div} + A_{abs} + A_{env}, \quad (9)$$

where *Adiv* is the geometric divergence (spherical spreading), dB; *Aabs* is the atmospheric absorption, dB; *Aenv* is the additional effects (ground reflection, refraction, turbulence).

The attenuation at distance r in decibels according to the formula from ISO 9613-2 is:

$$A_{div}(r) = 20\log\left(\frac{r}{r_0}\right) + 11, \quad (10)$$

where r_0=1 м is the reference distance.

Atmospheric absorption of pure tone based on ISO 9613-1

$$A_{abs}(f,r) = K \cdot \left(m_{O_2}(f) + m_{N_2}(f) + m_{class}(f)\right),$$

*дБ(*11)

where *K* is the coefficient (K=10lg(e)≈4.343 дБ); $m_{O_2}(f)$ is the molecular absorption by oxygen, 1/m; $m_{N_2}(f)$ is the molecular absorption by nitrogen, 1/m; $m_{class}(f)$ is the classical (viscous) absorption, 1/m.

In real conditions outside the city or in the city, reflection of waves from the surface of the earth or buildings should also be taken into account. An additional effect outside the city is associated with the propagation of direct and reflected waves from the ground according to the model. Sound pressure according to [15,16] is defined as

$$P(R,f) = \left(\frac{e^{-jkr_1}}{r_1} + \Gamma\frac{e^{-jkr_2}}{r_2}\right)P_0 \cdot e^{-\alpha(f)R_{гор}}, \quad (12)$$

where $R_{гор}$ is the horizontal distance to the UAV, m; $r_1 = \sqrt{R_{гор}^2 + (h_s - h_r)^2}$, $r_2 = \sqrt{R_{гор}^2 + (h_s + h_r)^2}$ is the path lengths of acoustic waves, m; $k = 2\pi f / c$ is the wave number; h_s is the source height, m; h_r is the receiver height, m; *Γ* is the reflection coefficient, which for dry soil is 0.7-0.9, for grass 0.4-0.7, for snow 0.2-0.5; *c* is the speed of sound, m/s.

In the city, according to ISO 9613-2, when calculating additional attenuation, buildings create acoustic barriers, the attenuation of which is calculated by the formula

$$A_{bar} = 10\log_{10}\left(3 + \frac{40 f\delta}{3c}\right), \quad (13)$$

where *δ* is the path difference between the direct and diffracted beam, m.

C. Research algorithm

Experimental verification of the developed model was carried out using the DJI Phantom 3 UAV. It has the following technical characteristics: engine rotation frequency - from 3000 to 10000 rpm (when hovering 5300-5400 rpm), number of engines - 4 pcs., number of blades - 2, propeller diameter - 239 mm, take-off weight - 1280 g, battery weight - 365 g, diagonal without propeller - 350 mm, frame material - carbon fiber and plastic, propeller weight - 13 g, engine weight - 58 g, flight speed - up to 16 m/s, number of engine pole pairs - 7, bearing ball diameter - 3.97 mm, bearing rolling circle diameter 7.35 mm, number of balls - 7. Based on these data and formulas (1)-(7), the spectral composition of acoustic noises of this UAV.

The results of our own measurements for the DJI Phantom 3, as well as studies published in [14,15,17], allowed us to determine the average statistical sound pressure level for the calculated spectral components of UAV noise. Analysis of the power spectral density (PSD) of the DJI Phantom 3 noise allowed us to conclude that the frequency peaks are not tonal, but have a quality factor corresponding to the type of noise component. So, for rotor noise, the quality factor is 12, for engine noise - 11, structural - 9, aerodynamic - 5. The formation of these frequency peaks was carried out by filtering broadband noise with a band-pass filter with the appropriate central frequency and bandwidth. Time realizations of UAV noise were formed with a length of 5s and a sampling frequency of 44100Hz. When creating realizations, 80 percent of the dataset corresponded to the movement of the UAV with a constant speed of movement from 0 to 16m/s. The last 20% corresponded to maneuvers when the speed of movement changes and, accordingly, the rotation frequency changes.

To simulate the propagation of acoustic waves in the atmosphere, the following were performed: direct Fourier transform of the noise realization, attenuation of frequency components according to the distance between the UAV and the microphone, inverse Fourier transform. The attenuation calculation was performed for the distance range from 10 to 100m, humidity 70%, air temperatures from -10ºC to 30ºC, type of terrain – outside the city and the city. The addition of external noise was implemented in two ways: as the addition of white noise and as the addition of real noise outside the city and in the city. Thus, a dataset of 2050 implementations of UAV noise and a similar number of natural and industrial noise implementations was formed. An example of the temporal implementation of DJI Phantom 3 noise and spectral components is shown in Figure 1.

Using the generated dataset, a convolutional neural network was trained [18,19]. The network consisted of two convolutional layers with 32 and 64 cores, as well as three fully connected layers with 256, 128, 2 neurons. MFCC coefficient matrices of size 32x32 were fed to the network input. Training continued for 100 epochs. After training the trained neural network, the recognition efficiency of real DJI

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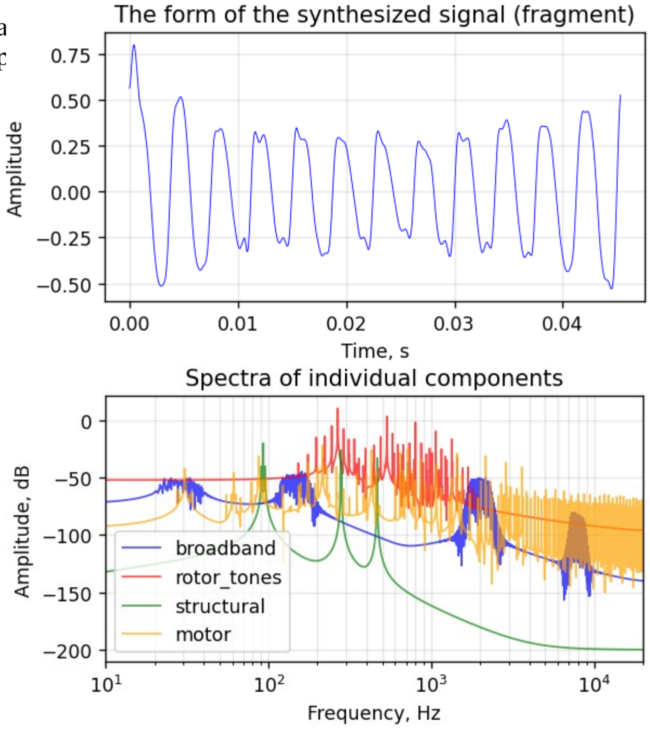

Fig. 1 – Example of UAV noise temporal realization and spectral components

III. Research Results

The neural network training was completed with a recognition efficiency value of 99.93% for the validation part of the dataset. After processing the testing dataset, it was possible to achieve a probability of correct recognition of 0.72 when superimposing white noise on UAV noise and a probability of 0.84 when superimposing real natural and industrial noise.

IV. Conclusions

Testing the trained neural network on synthetic implementations of the developed mathematical model of the spectral composition of UAV noise confirmed the model's performance. Adding synthetic implementations of external white noise to UAV noise showed the inefficiency of such an approach for training neural networks. A significantly better result (probability of correct recognition 0.84) was shown by the approach of superimposing real noise implementations recorded outside the city and in the city. The developed model loses in the probability of correct recognition to the classical approach when training is performed on real recordings of UAV noise. Therefore, further improvement of this model is necessary, namely, more accurate determination of radiation levels at the fundamental frequencies of the UAV's own acoustic radiation.

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