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SELF-LEARNING INFORMATION TECHNOLOGY FOR DETECTING RESPIRATORY DISORDERS IN HOME CONDITIONS

Introduction. In connection with the COVID-19 pandemic, it is important to start treatment promptly in case of a threat of developing viral pneumonia in a patient. The solution to this problem requires the creation of new means for detecting respiratory disorders with a minimum probability of "missing the target". At the same time, it is equally important to minimize visits to medical institutions by healthy patients because of the danger of their contact with possible carriers of coronavirus infections, that is, to minimize the likelihood of a "false alarm".

Purpose of the article is to develop a method that allows a patient to signal at home about the advisability of contacting a medical institution for an in-depth examination of the respiratory system, and to assess the possibility of implementing this method on a smartphone using a built-in microphone.

Methods. A distinctive feature of the proposed approach lies in the construction of a personalized standard of normal respiratory respiration for a particular patient based on self-learning from a finite sample of observations at home and in comparison, based on original computational algorithms of phonospirograms of sound signals of the following observations with the standard.

Results. A prototype of information technology has been developed that will provide home alarms about possible respiratory disorders, requiring consultation with a doctor and the need for an in-depth medical examination.

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It is shown that the construction of a personalized standard of normal breathing can be carried out based on the use of a set of original computational procedures for a finite sample of realizations, independently registered by the user using a microphone built into a smartphone. The algorithm for constructing a standard is based on digital processing of a matrix of paired distances between phonospirograms of the final training sample of observations.

Conclusions. *A software application that provides the implementation of the proposed computational procedures can be implemented on a smartphone of average performance running the Android operating system.*

Keywords: *respiratory noises, intelligent IT, computational procedures, smartphone.*

INTRODUCTION

The method of auscultation (listening to respiratory noises) has been used in medical practice for the diagnosis of respiratory diseases for over 200 years. According to modern concepts, sound phenomena that carry information about functional disorders of the respiratory system arise in the larynx and trachea as a result of turbulent air movement [1, 2]. Sound vibrations are transmitted to the chest at the location of the stethoscope and form various types of breathing noises, the subjective analysis of which allows the doctor to assess the state of the respiratory system and carry out differential diagnostics of a number of diseases.

It is clear that the subjective analysis of breathing sounds significantly depends on the doctor's experience and does not allow obtaining objective quantitative characteristics of breathing noises [3]. In the middle of the last century, automated systems for assessing respiratory sounds appeared in clinical practice, which provided support for making diagnostic decisions [4–6].

The first such systems used only analog electronics (microphones, amplifiers, oscilloscopes and tape recorders), with the help of which it was possible for the first time to register respiratory sounds arising from breathing. These studies made it possible to formulate basic concepts and determine the main classes of respiratory noise in a healthy person and in pathologies that are still used by pulmonologists.

The development of digital computing technology has laid the foundation for computer systems for analyzing breathing sounds [7], which use special sensors with high sensitivity in a wide frequency range, including frequencies that are not audible with a stethoscope. One of the examples of such systems is the domestic phonospirograph Kora-03MI, developed at the Institute of Hydromechanics of the National Academy of Sciences of Ukraine. With the help of it, by the methods of spectral-temporal analysis, it was possible to objectify the assessment of complex sound signals on the basis of original auscultatory signs [8, 9].

Undoubtedly, the use of such software and hardware complexes in medical practice significantly increases the reliability of diagnostic solutions. At the same time, another class of information technologies for processing breathing sounds is also required. The nature of the course of a number of diseases presupposes a distributed system of health services delivery, when home supervision and treatment becomes important. Note that bringing medical devices closer to the patient is one of the main tasks of digital medicine [10].

This task is of particular relevance in connection with the **COVID-19** pandemic, since, on the one hand, it is important to timely diagnose and begin treatment of a patient with a threat of viral pneumonia (to minimize the likelihood of "missing the target"), and, on the other hand, to prevent unreasonable visits to

medical institutions and contacts with possible carriers of coronavirus infection (to minimize the likelihood of "false alarm").

The purpose of the paper is to develop a method that allows a patient to signal at home about the advisability of contacting a medical institution for an in-depth examination of the respiratory system and to evaluate the possibility of implementing this method on a smartphone using a built-in microphone.

BRIEF DESCRIPTION OF RESPIRATORY NOISES

Before proceeding directly to the solution of the problem, let us give a brief description of the main sounds of breathing known from the literature [11–15]. For this purpose, we will construct phonospirograms reflecting changes in the spectral characteristics of respiratory noise during respiration, using sound files stored on the Internet [16] (Fig. 1–3).

During auscultation of the lungs of a healthy person, the so-called vesicular breathing is heard in the frequency range of 18 – 360 Hz. In this case, the highest sound volume is concentrated in the range of 50 – 70 Hz, and the sound energy on inhalation significantly exceeds the sound energy on exhalation and is audible only in the initial period of the oscillation decay phase (Fig. 1).

In some organic diseases, for example, in patients with emphysema of the lungs, breathing, although it remains vesicular, is significantly weakened. On the other hand, with bronchitis and bronchial asthma, the so-called rigid vesicular breathing is observed. In this case, the sound energy is heard up to 600 Hz not only during inhalation, but throughout the entire exhalation.

The second type of main respiratory noise is *bronchial breathing*, which is several times higher than vesicular and reaches 700 – 1400 Hz, and sometimes more (up to 5000 Hz), and on exhalation the energy of bronchial respiration is often higher than on inhalation (Fig. 2).

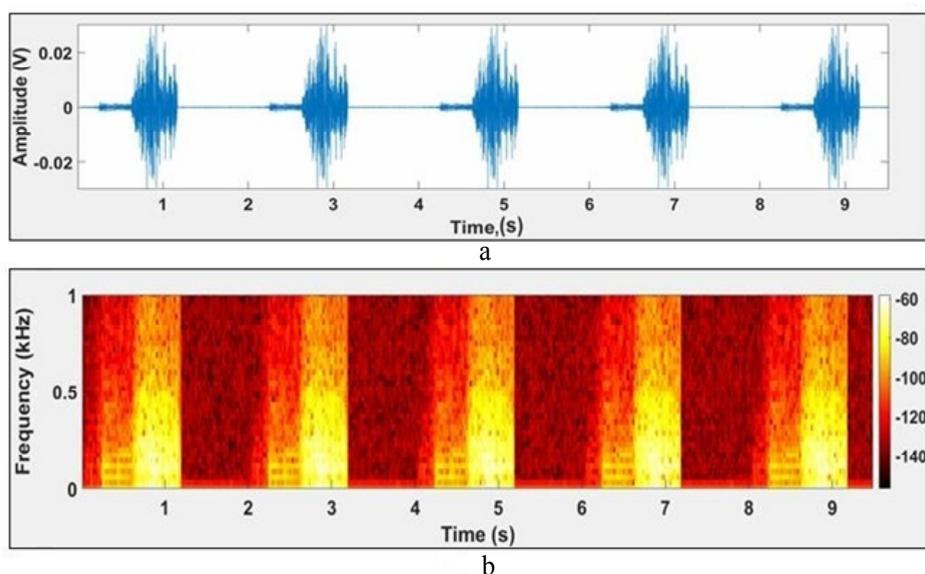


Fig. 1. Sound signal of vesicular respiration (a) and the corresponding phonospirogram (b)

In a healthy person, the sound of bronchial breathing can be heard only with auscultation of the trachea and quite rarely in the 2–3 intercostal space. The appearance of the sound of bronchial breathing at any other point of auscultation of the lungs indicates pathology.

A type of bronchial breathing is called ***amphoric breathing***, which is formed when a cavity is formed in the lungs, which is communicated by the bronchi. Such breathing is more pronounced on exhalation and is characterized by relatively high frequencies (from 500 to 5000 Hz) with a pronounced echo.

Additional respiratory noises, which are heard both on inhalation and exhalation against the background of the main respiratory sound, carry important diagnostic information. One of the types of additional respiratory noises is the so-called wheezing (dry and wet, Fig. 3), the appearance of which indicates a pathological process in the lungs, bronchi or in the pleura.

According to [17], dry rales are visualized on phonospirograms in the form of an ensemble of harmonics, and wet ones are short-term broadband impulse signals.

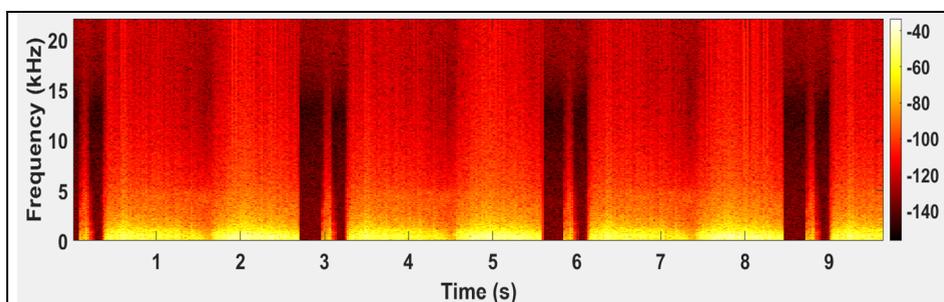
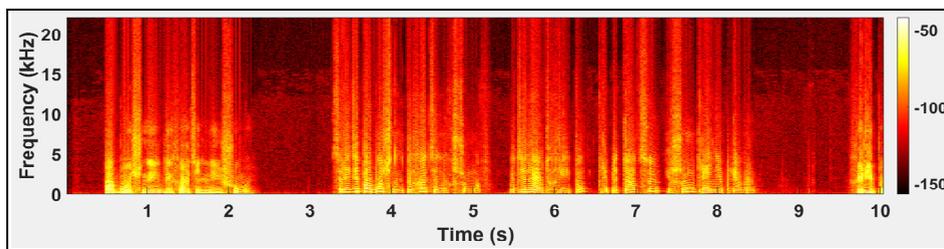
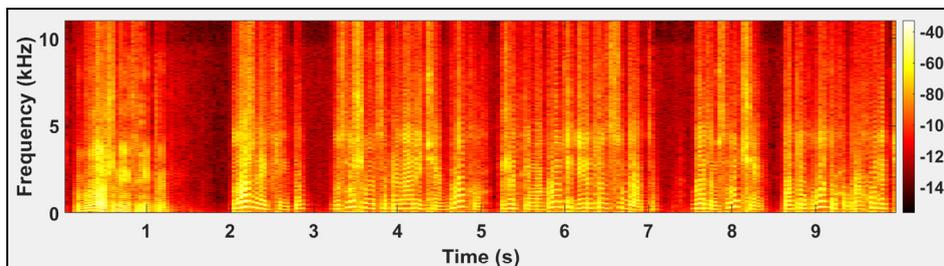


Fig. 2. Phonospirogram of bronchial respiration



a



b

Fig. 3. Phonospirograms of dry (a) and wet (b) wheezing

Another type of additional respiratory noise is *crepitus*, which occurs at the height of inspiration and sounds like a small crackle. Unlike wheezing, crepitus is audible only on inspiration, and its volume does not change after coughing up.

CONCEPTUAL IDEA OF THE PROPOSED INFORMATION TECHNOLOGY

From the above brief and far from complete description, we can conclude that the differential diagnosis of respiratory diseases based on the sounds of breathing is far from a simple problem, the solution of which involves a subtle analysis of the time-frequency characteristics of phonospirograms observed at certain points in the patient's chest.

We set a simpler goal: for a specific patient, only to signal about possible respiratory disorders by sound signals observed using the built-in microphone of a smartphone without classifying the type of such a violation.

The conceptual idea underlying the proposed information technology (IT) develops the previously proposed approach to the assessment of cardiac activity, based on the principles of personalized diagnostics [18].

Let it be possible to conduct IT “training” for a particular patient over a sufficiently long period of time with the normal functional state of the respiratory system. To do this, using the built-in microphone of the smartphone, we register a certain amount of N_0 respiratory noises at a certain point of the chest, construct phonospirograms $\Psi_1, \dots, \Psi_{N_0}$ of these measurements.

Each individual phonospirogram is a function

$$\Psi = \Psi(f, t), \tag{1}$$

where Ψ — energy (level) of sound signal with frequency $f \in F$ at the moment $t \in T$. Here $F = [f_1, f_2]$ is a range of recorded frequencies in a given observation interval $T = [t_1, t_2]$.

The proximity of two phonospirograms Ψ_μ and Ψ_ν will be estimated by the magnitude

$$\tilde{L}_{ij} = \frac{1}{K} \sum_{k=1}^K |\Psi_\mu^{(k)}(f, t) - \Psi_\nu^{(k)}(f, t)|, \tag{2}$$

representing the average difference in sound energy $\forall k \in F \times T$.

For a correct assessment of the proximity of phonospirograms, let us normalize and synchronize them in time. Several methods of such synchronization have been investigated, one of which is reduced to the transition from distance (2) to a modified distance

$$L_{ij} = \min_{\rho=0, \dots, \Theta} \frac{1}{K} \sum_{k=1}^K |\Psi_\mu^{(k)}(f, t) - \Psi_\nu^{(k)}(f, t - \rho)|, \tag{3}$$

where Θ — maximum permissible time shift of characteristic points of phonospirograms.

Distances (3) form an area in metric space that defines the *personal norm* of the respiratory system of a particular patient. The location of the current observation in relation to this area allows making decisions about the state of the user's respiratory system (Fig. 4).

Let's construct a matrix of paired distances $L_{\mu\nu}$ between μ -th ($\mu = 1, \dots, N_0$) and ν -th ($\nu = 1, \dots, N_0$) phonospirograms Ψ_μ and Ψ_ν training sample.

$$\Lambda = \begin{pmatrix} L_{11}, & L_{12}, & \dots, & L_{1N_0} \\ L_{21}, & L_{22}, & \dots, & L_{2N_0} \\ & & \dots & \\ L_{N_01}, & L_{N_02}, & \dots, & L_{N_0N_0} \end{pmatrix} \quad (4)$$

Matrix row Λ , the sum of the elements of which is minimal will determine the reference (most characteristic) phonospirogram of the given patient

$$S_0 = \arg \min_{1 \leq \nu \leq N_0} \sum_{\mu=1}^{N_0} L_{\mu\nu} \quad (5)$$

since it is at the minimum average distance from all other phonospirograms of the training sample.

As a result, by distance L_{n0} between the observed phonospirogram S_n and reference S_0 you can make a decision according to the scheme:

$$\text{personal norm if } L_{n0} \leq L^0; \quad (6)$$

$$\text{suspected respiratory violation if } L_{n0} > L^0; \quad (7)$$

where L^0 — some threshold value.

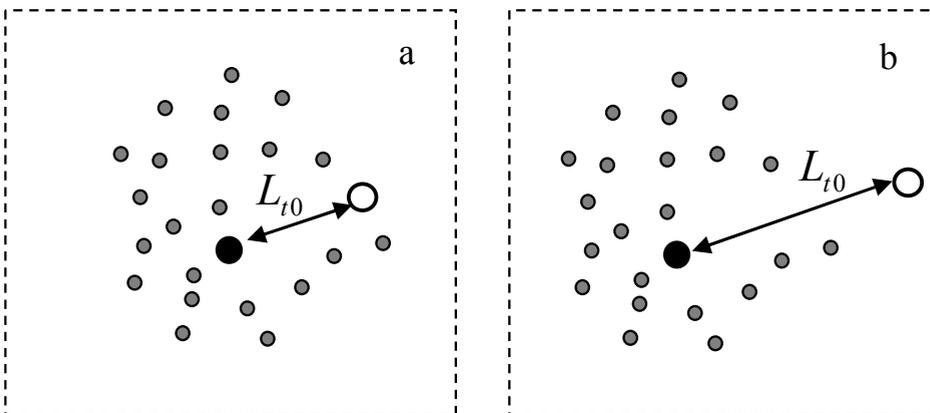


Fig. 4. Areas of the personal norm of phonospirograms: trainings (gray dots); reference (black point) and current (white point)

SIMULATION RESULTS

Let us present the results of an experimental study of the computational procedures necessary for the implementation of the proposed approach, which were carried out using the MATLAB R2019b system.

Breathing sounds were recorded using a microphone built into the smartphone, which was applied to the volunteer's chest (Fig. 5). The recording of the sound signal $y(t)$ with a sampling rate of $F_D = 48$ KHz was carried out in a closed room in the absence of extraneous noise.

To determine the spectral components of the $y(t)$ signal, the *Frigo-Johnson* [19] procedure was used, which is still recognized as one of the best procedures implementing the fast Fourier transform (FFT) algorithm.

Since the signal $y(t)$ of respiratory noise is non-stationary and has a complex time-frequency organization, the *Short-Time Fourier Transformation* [20] algorithm was used to construct phonospirograms. In accordance with this algorithm, the observation interval $T = [t_1, t_2]$ of the signal $y(t)$ was divided into local time sections (frames), within which the signal is assumed to be stationary. For each such area, spectral components are determined based on the FFT procedure. As a result, a phonospirogram is formed

$$\Psi(f, t) = \int_{\tau} y(t)w(t - \tau)e^{-2\pi i f t} d\tau \quad (8)$$

depending on both the frequency f and the time t , where $w(t - \tau)$ is the window function.

In the experiments, the total observation interval $T = [t_1, t_2]$ was 23 s, which was divided into $N \approx 200$ frames of the same duration.

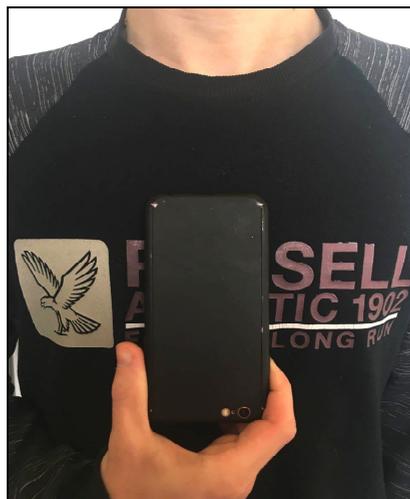


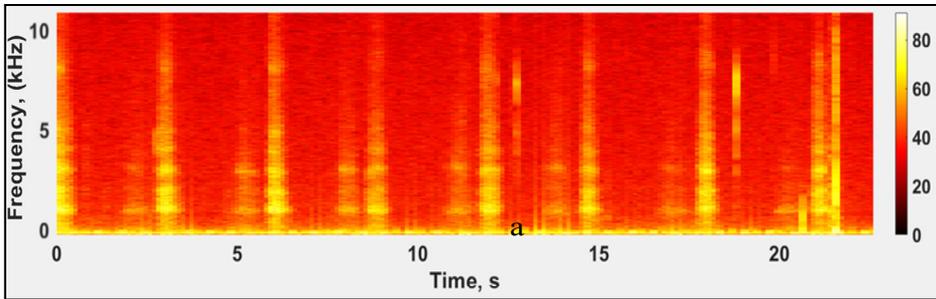
Fig. 5. Registration of respiratory sound using a smartphone

To simplify calculations, using an additional procedure, the sets of values Ψ , F , T were divided into elementary cells $\delta_\Psi\Psi$, δ_FF , $\delta_T T$ of optimal sizes. This made it possible, without a significant loss of accuracy, to estimate the distances between phonospirograms not by all points of $k \in F \times T$, but within the selected cells (Fig. 6) and thereby more than 15 times reduce the computation time.

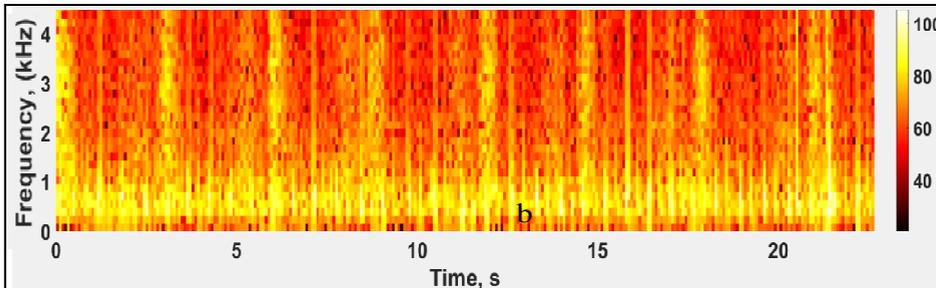
Experiments have shown that the integral characteristics of the phonospirogram images of a particular test subject change little over time. Therefore, the construction of a reference phonospirogram S_0 can be carried out using a small number of phonospirograms. Of course, the training phase should be carried out only in the absence of clinical signs of respiratory disorders.

Fig. 7 shows a series of phonospirograms of a healthy volunteer at the age of 21 years, which were registered within five days. These phonospirograms were used to construct a matrix Λ of paired distances $L_{\mu\nu}$:

$$\Lambda = \begin{pmatrix} 0 & 1,0916 & 1,3958 & 1,1927 & 1,2536 \\ 1,0916 & 0 & 1,3421 & 1,1800 & 1,2530 \\ 1,3958 & 1,3421 & 0 & 1,4864 & 1,3968 \\ 1,1927 & 1,1800 & 1,4864 & 0 & 1,3267 \\ 1,2536 & 1,2530 & 1,3968 & 1,3267 & 0 \end{pmatrix} \quad (9)$$



a



b

Fig. 6. Images of the original (a) and coarse (b) phonospirograms

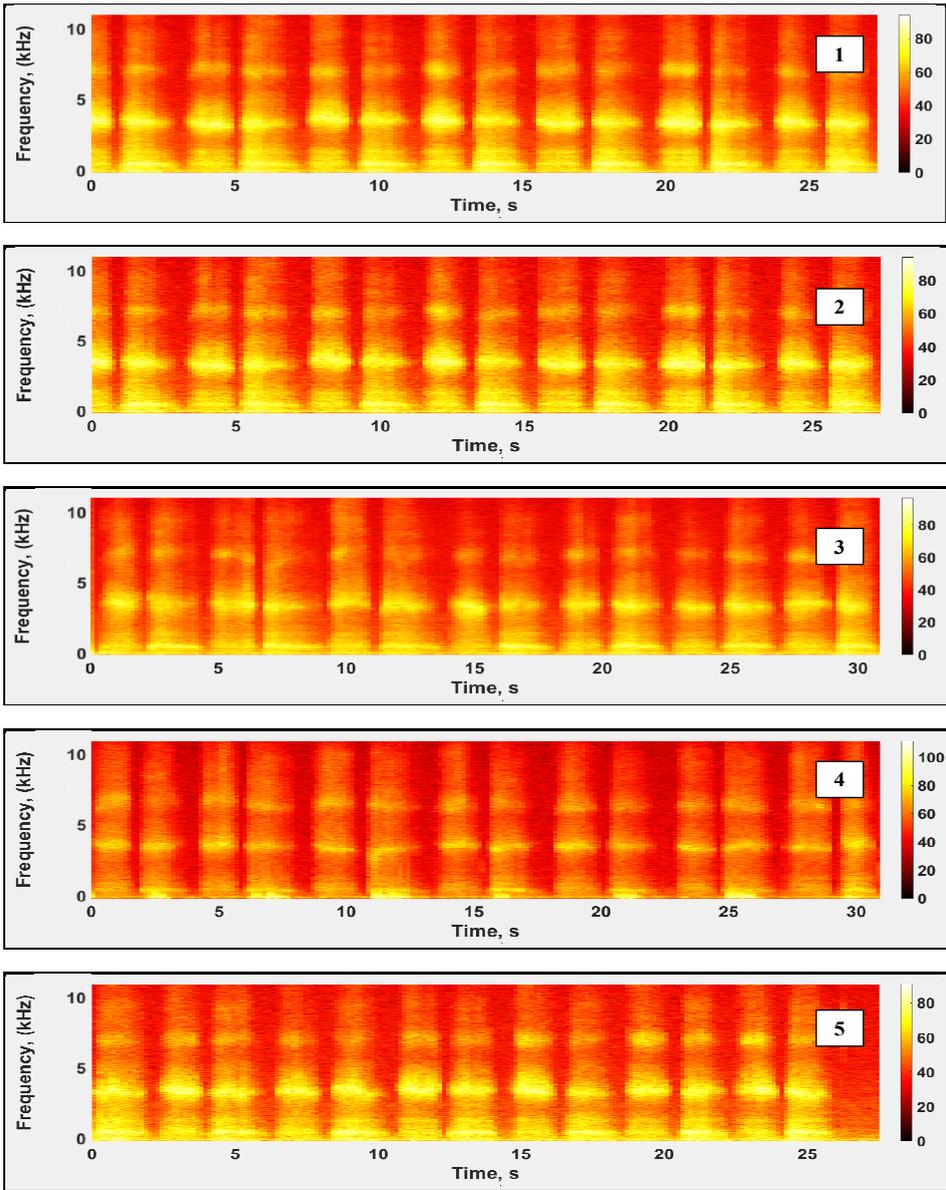


Fig 7. Training selection of phonospirograms of a healthy volunteer

Applying condition (4) to the elements of matrix (8), it was determined that phonospirogram № 1 can be considered a reference according to the results of training for a given patient. The same phonospirogram was recognized as a reference and when processing coarse phonospirograms.

The reference phonospirogram S_0 , built at the training stage for a specific user, will be used in the decision rule (6), (7). To assess the efficiency of the rule, a phonospirogram of the same volunteer in case of respiratory impairment is required. In view of the lack of such data, we have developed a simplified model for constructing an artificial phonospirogram that simulates a patient's respiratory disorder.

In the scientific literature, there are various approaches to the construction of mathematical models of respiratory sounds in norm and disease [21–25]. These studies form the informational basis of rather complex computer systems that provide decision support in the differential diagnosis of pulmonary diseases [26–30].

However, to solve the problem that we have set ourselves, there is no need to conduct a fine analysis of respiratory noise. It is enough only to detect the characteristic changes in the phonspirogram of a particular patient, which can be used as a predictor of the occurrence of a respiratory disorder.

In accordance with generally accepted concepts [31], the human respiratory system is a tracheobronchial tree - a branching of the Weibel pathways (Fig. 8). Noises in different parts of such a system are associated with nonlinear effects caused by the transitions of laminar to turbulent flow both in the air flow itself and in the interaction of the flow with the changing boundaries of the channel [32].

Based on the analysis of information from the available literature, the following requirements for a simplified model of the formation of pathological respiratory sound can be formulated:

- in the event of respiratory disorders, characteristic additional respiratory sounds occur, which are mainly heard in the expiration phase of breathing;
- additional breathing sounds are located in the frequency band $\Omega = 800 - 1200$ Hz (Fig. 9);
- the energy of individual spectral components of the additional noise can exceed the energy of the spectral components of the sound signal characteristic of vesicular respiration (Fig. 9).

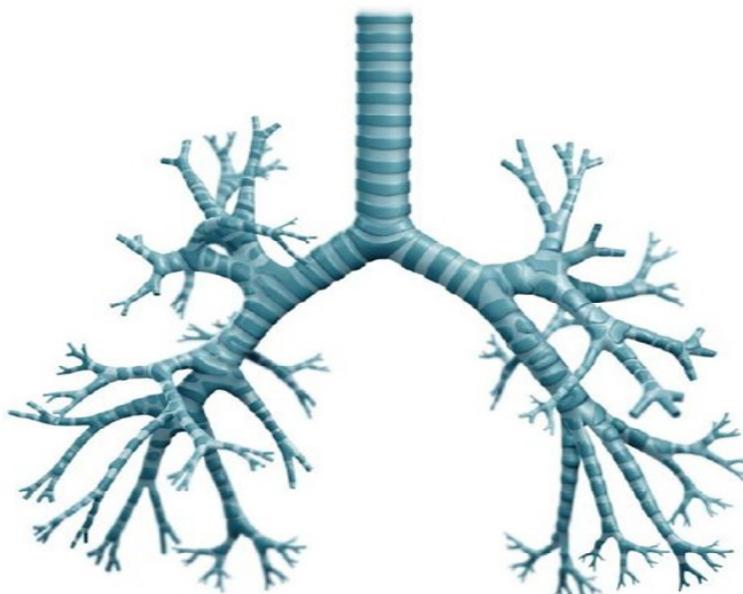


Fig. 8. Diagram of the branching of the Weibel pathways of the respiratory system [31]

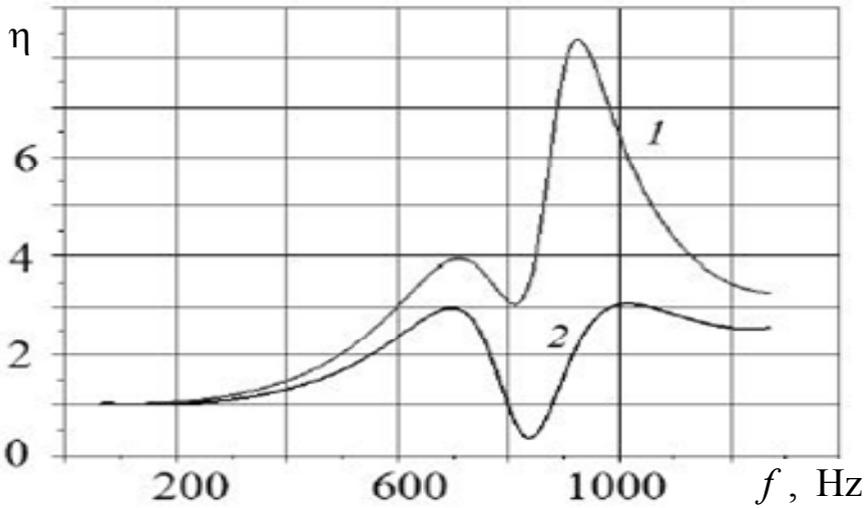


Fig. 9. Differences in the relative frequency characteristics of η on audio signals sick (1) and healthy 2 patients (according to [31])

Taking these requirements into account, let us present a model of pathological respiratory noise in the form of an additive mixture of a real sound signal y_0 of a particular patient during vesicular breathing and a certain sum of S harmonic components with fixed frequencies $\omega_s \in \Omega$, given amplitudes a_s and phases φ_s :

$$y(t) = y_0(t) + \begin{cases} 0, & \text{if } t \in T_0, \\ \sum_{s=1}^S a_s \cos(\omega_s t + \varphi_s), & \text{if } t \notin T_0, \end{cases} \quad (10)$$

where $\Omega = 800 - 1200$ Hz is the frequency range of noise components on exhalation, which are characteristic of additional noises in respiratory disorders, and $T_0 = [t_1^{(1)}, t_2^{(1)}] \cap [t_1^{(2)}, t_2^{(2)}] \cap \dots \cap [t_1^{(N)}, t_2^{(N)}]$ is the combination of time intervals that correspond N to successive inhalation cycles on the signal y_0 .

As a result, a signal $\Omega = 800 - 1200$ Hz is formed, imitating the violation of vesicular respiration, which can be used to construct an artificial phonospirogram of a respiratory disorder in a particular patient (Fig. 10).

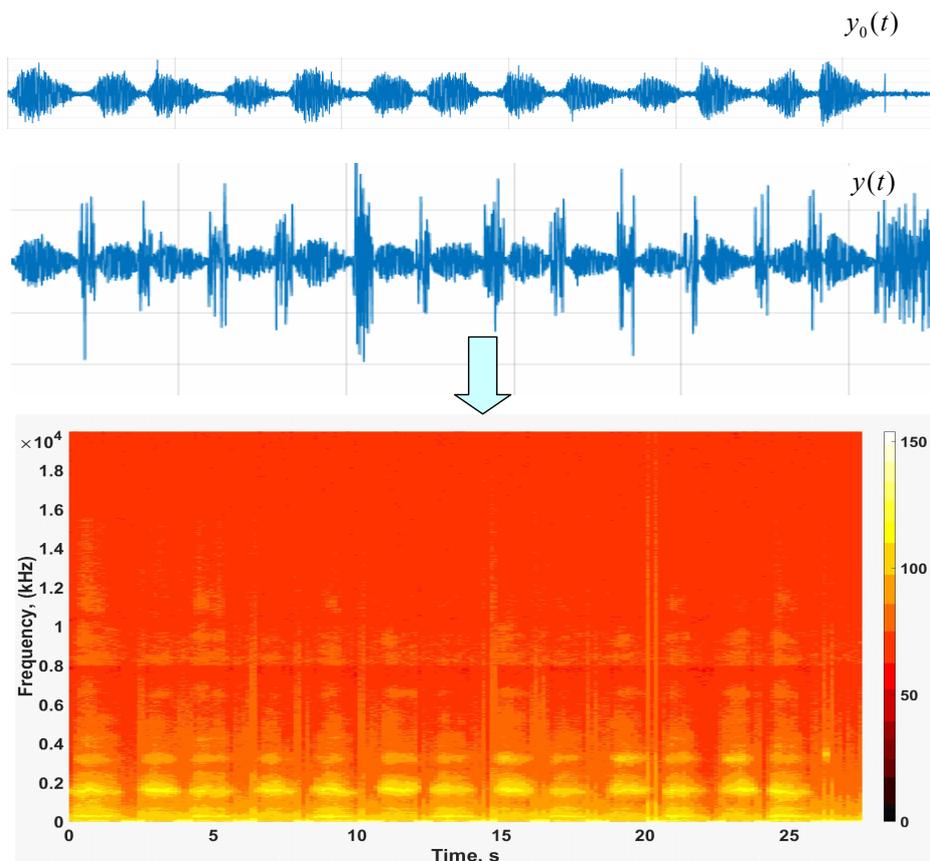


Fig. 10. Construction of an artificial phonospirogram

Model experiments showed that the average distance between the photoplethysmogram, simulating a respiratory disorder, and the photoplethysmogram of a healthy volunteer (interclass distance) was more than five times greater than the intraclass distance between photoplethysmograms during normal respiratory respiration. The established fact made it possible to switch to software implementation of the proposed IT on a smartphone.

SOFTWARE IMPLEMENTATION OF IT ON A SMARTPHONE

The software application is developed in the Java programming language using the Android Studio 4.1.2 integrated development environment. The program is designed to work under the operating system Android 4.1 and higher. The visualization of graphical information was carried out using the Com.jjoe64 library: graphview: 4.2.2.

The program implements four main modes (Fig. 11):

- "Training";
- "Analysis";
- "Demo";
- "Setting".

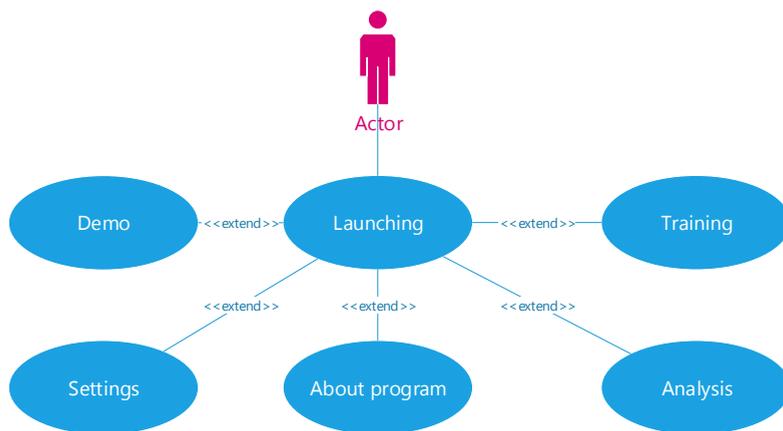


Fig. 11. Simplified Use Case diagram in UML notation

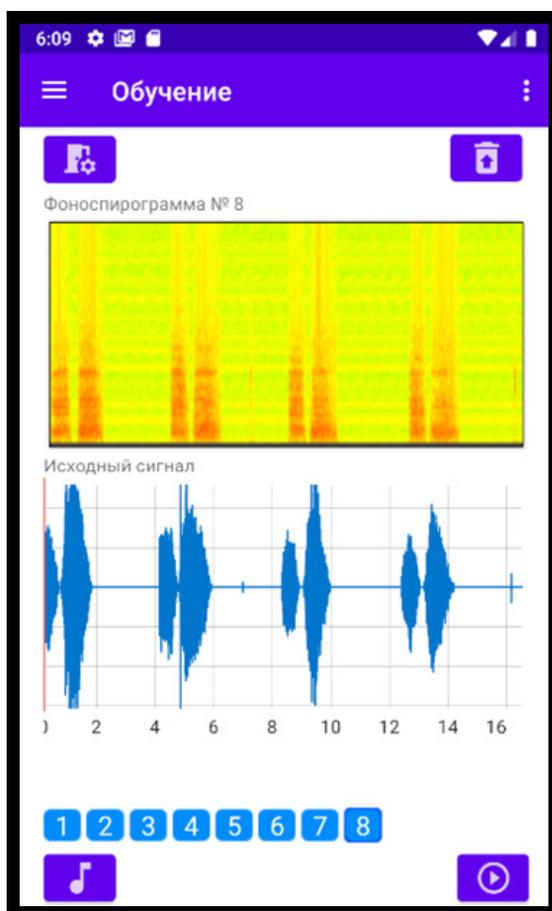


Fig. 12. Working window of the program in the "Training" mode

The "Training" mode provides:

- recording into the smartphone's memory a series of sound signals recorded by the built-in microphone when the smartphone is placed on the user's chest (Fig. 5);
- listening to registered sound files;
- construction of phonospirograms of registered signals based on the *Short-Time Fourier Transformation* algorithm;
- determination of the reference phonospirogram based on the analysis of the matrix (4) of paired distances between the phonospirograms of the training sample.

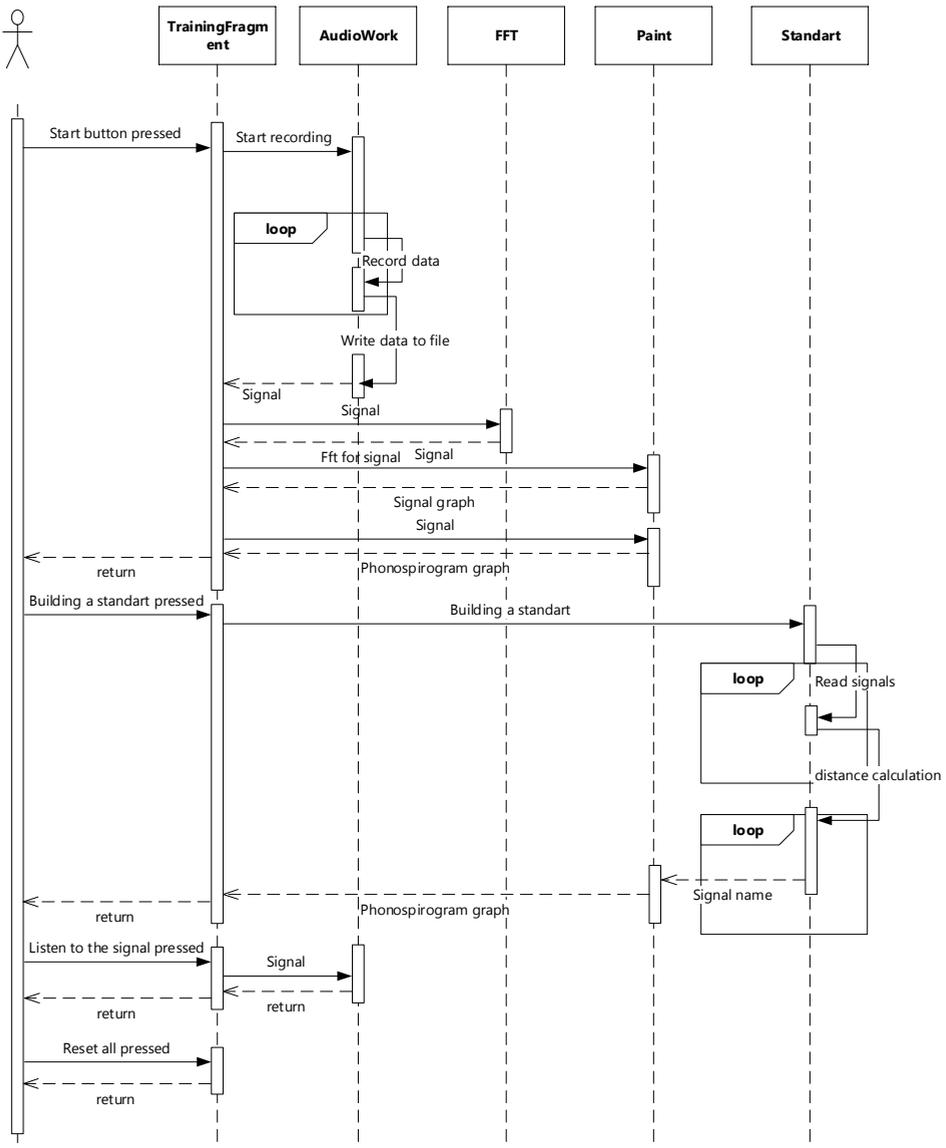


Fig. 13. The Sequence diagram of "Training" mode

The program implements a friendly interface (Fig. 12), which creates convenience for the user in the process of registering sound files. In particular, the rate of breathing is controlled by the software metronome, which signals the user to take another deep breath and exhale. The preset breathing rate is adjusted in the "Settings" mode.

The sequence of operations in the "Training" mode is illustrated by the sequence diagram (Fig. 13).

In the "Analysis" mode, a comparison of the current phonospirogram recorded during the observation period with a personalized standard built in the "Training" mode is provided. The registered signal is displayed on the screen and can be listened to using a smartphone. The screen also displays the current and reference phonospirogram.

On the basis of automatic comparison of the current and reference phonospirograms, the analysis result is formed in accordance with the proposed rule (6), (7). The analysis result is also duplicated by an audio message.

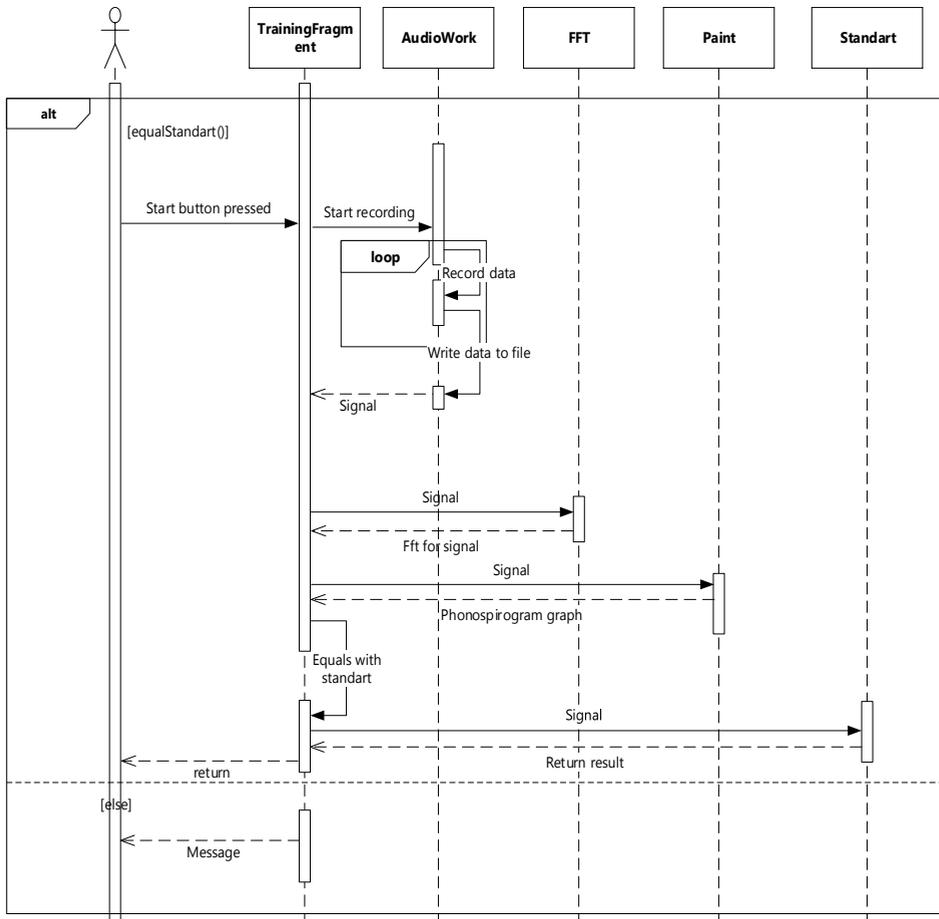


Fig. 14. The Sequence diagram of "Analysis" mode

The sequence of operations is illustrated by the diagram shown in Fig. 14. For a simplified demonstration of the functions of the program, the "Demo" mode is implemented, which uses previously prepared files of the reference phonospirogram and phonospirograms built from normal and pathological sound files using a simulator (10).

Further studies are planned to focus on the refinement of threshold values, the construction of decision rules and the assessment of the reliability of decisions made on respiratory noise recorded in groups of healthy patients and verified patients.

CONCLUSION

The article proposes an approach to the construction of information technology that will signal the user at home about possible respiratory disorders and the need to visit a doctor for a more complete examination. A distinctive feature of the technology is the formation of a personalized norm for a specific user (reference phonospirogram) based on a self-learning procedure by results of multiple measurements of the user's breathing, recorded using the built-in microphone of a smartphone.

It is shown that the implementation of procedures for constructing personalized phonospirograms of the user's respiratory noise based on the Short-Time Fourier Transformation method and digital processing of phonospirograms can be implemented on an average performance smartphone running the Android operating system.

It is advisable to continue research on representative samples of observations.

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САМОНАВЧАЛЬНА ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ ДЛЯ ВИЯВЛЕННЯ РЕСПІРАТОРНИХ ПОРУШЕНЬ У ДОМАШНІХ УМОВАХ

Вступ. У зв'язку з пандемією COVID-19 є важливим своєчасно почати лікування у разі загрози розвитку у пацієнта вірусної пневмонії. Розв'язання цього завдання вимагає створення засобів для виявлення респіраторних порушень з мінімальною ймовірністю «пропуску цілі». Водночас не менш важливо звести до мінімуму відвідування медичних установ здоровими пацієнтами через небезпеку їхнього контакту з можливими носіями коронавірусної інфекції, тобто мінімізація ймовірності «помилкової тривоги».

Мета статті — розробити метод, який дає змогу в домашніх умовах сигналізувати пацієнту про доцільність звернення до медичного закладу для поглибленого обстеження системи органів дихання, та оцінити можливість реалізації цього методу на смартфоні з використанням вбудованого мікрофона.

Методи. Відрізнена особливість запропонованого підходу полягає у побудові персоналізованого еталона нормального респіраторного дихання конкретного пацієнта на основі самонавчання за кінцевою вибіркою спостережень у домашніх умовах і у порівнянні на основі оригінальних обчислювальних алгоритмів фоноспірограмм звукового сигналу наступних спостережень з еталоном.

Результати. Розроблено прототип інформаційної технології, яка забезпечуватиме у домашніх умовах сигналізацію про можливі респіраторні порушення, що потребують консультацій з лікарем і необхідність поглибленого медичного обстеження.

Показано, що побудову персоналізованого еталона нормального респіраторного дихання може бути здійснено на основі використання сукупності оригінальних обчислювальних процедур за кінцевою вибіркою реалізацій, самостійно зареєстрованих користувачем за допомогою вбудованого в смартфон мікрофона. Алгоритм побудови еталона оснований на цифровому обробленні матриці парних відстаней між фоноспірограмами кінцевої навчальної вибірки спостережень.

Висновки. Програмний застосунок, що забезпечує реалізацію запропонованих обчислювальних процедур, може бути здійснено на смартфоні середньої продуктивності під керуванням операційної системи Android.

Ключові слова: респіраторні шуми, інтелектуальна ІТ, обчислювальні процедури, смартфон.