Methods of COVID-19 Diagnosis Accuracy Improving by Human Head Micromovement Video Processing Using Vibraimage Technology and Artificial Intelligence

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Abstract: *Digital processing methods of human head video by vibraimage technology are outlined, including various approaches to increasing the information content of biometric data. Considered different settings for Discrete Vibraimage Transform (DVT). The replacement of local discretization of human movements to cloud discretization is considered, including a frequency range of (5–10) Hz and time intervals of 25–30 frames of inter-frame difference accumulation to improve the accuracy of COVID-19 diagnostics. Method has been explored to increase the number of measured behavioral parameters to ensure not less 90% accuracy for COVID-19 diagnosis. The method for separate artificial intelligence training by the behavioral parameters measured at the beginning and the end of the disease is proposed. Comparative studies have been carried out to ensure the required accuracy of diagnosing a disease and a hypothesis has been proposed for the possibility of an arbitrary disease diagnosis by human head micromovement analysis based on vibraimage technology and artificial intelligence.*

Keywords: *COVID-19, vibraimage, behavioral parameters, video image, artificial neural networks, artificial intelligence, vestibular system.*

Introduction

At each vibraimage technology conference, were presented the reports about operation principles of vibraimage technology, considering it from the different points of view and opening up new possibilities for biometric information processing. At the 1st conference, the history of vibraimage technology development was described, based on the biological principles proposed by Sechenov, Darwin, Freud, Pavlov, Jung, Bernstein, Lorenz, Mira-y-Lopez, Gardner used to understand and develop vibraimage technology (Minkin, Nikolaenko, 2008; Minkin, 2007; 2018). At the 2nd conference, a review of vibraimage technology applications was published (Minkin, 2019a), since the use of vibraimage technology to solve various technical, psychological, biological or medical problems requires the implementation of different approaches to system settings. At the 3rd conference, the concept of vibrapsychology and vibramedicine was proposed as independent scientific branches (Minkin, 2020a). On the 4th conference, four generations of vibraimage systems were considered

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based on various metrological principles for constructing measuring systems (Minkin, 2021a). Technical base of vibraimage technology is information theory (Hartley, 1928; Kolmogorov, 1968) and cybernetics (Wiener, 1948; Shannon, 1948). We consider a person as cybernetic system having constant feedback inside and between physiological system components (Novoseltsev, 1978) and any pathological process as disease have influence to normal physiology like interference has influence to information signal.

It seemed that all aspects of the vibraimage technology had already been sorted out and nothing new could be invented. But it turned out that life constantly poses new challenges for us, and to solve them, is necessary to significantly develop the vibraimage technology and extract more information from video image than it happened before. Even in the first monograph on vibraimage, was shown that the possibility of biometric information capturing is limited by hardware performance (Minkin, 2007), and, practically, all vibraimage programs were built on the basis of average performance computers available to users. At the same time, the first versions of vibraimage programs simultaneously measured the parameters of a person's psychophysiological state (PPS) using different movement settings (Minkin, Kachalin, 2020) for the interframe difference accumulation N = (2, 10, 100) and frame rate f = (5, 30 f/s). Most of PPS parameters were measured at a lower 5 Hz frequency in order to reduce the load on the processor and increase the signal-to-noise ratio when measuring micromovements of a human head. Thus, initially in the technology of vibraimage the following principles were formulated to increase the information content of the data obtained from the video image:

1. Discretization principle. The frequency of video transformation (movement discretization) to vibraimage parameters should be maximum at the minimum level of video image noise. From a real video image of a human head is impossible to separate noise from movement. Naturally, an increase of transformation frequency leads to an increase in noise and a decrease movement information; the frequency range informative for the analysis of micromovements of the human head is 5–15 Hz, depending on the illumination and camera sensitivity (Minkin, 2007).

2. Conformity principle. The period of interframe difference accumulation must coordinate with the period of the analyzed physiological process, the mismatch between the accumulation time of the interframe difference with the analyzed physiological or psychophysiological process leads to the loss of biometric information. In current programs, the accumulation period varies from 2.5 to 20 seconds, depending on the problem being solved (Minkin, 2020c; Minkin, 2021b; Minkin, Myasnikova, 2018).

3. Principle of optimality. The number of measured behavioral parameters (BP) should be minimally sufficient for the analysis of the studied physiological process or response to the presented stimulus. In current vibraimage programs, the number of measured parameters varies from 1 to 10,000 depending on the aim being solved (Minkin, 2020c; Minkin et al., 2020; Akimov, Minkin, 2021; Minkin, Akimov, 2022).

In various applications, the main settings of vibraimage systems responsible for biometric information processing vary within a fairly wide range. The possibility of vibraimage information content increasing of thermal image using (Kolobashkina, Alyushin, 2020) seems to be quite controversial, since it requires the collection of significant statistics to develop new equations and determine the norms for the measured BP (Akimov, Didenko, Minkin, 2020). Moreover, the thermal image loses to the standard video in terms of noise and contrast, and these parameters determine the quality of vibraimage. The purpose of this study is to determine the criteria for biometric information content of video and to study new approaches for obtaining additional information a human head video image to ensure COVID-19 and other diseases at least 90% diagnosis accuracy by 20 seconds testing.

Materials and Methods

The hypothesis that COVID-19 can be diagnosed by video image of a human head analyzing was put forward by us back in 2020 year and confirmed by BP measurements using AI training on videos of COVID-19 patients and controls during a 60-second test (Minkin, Bobrov, 2020; Minkin et al., 2020). Later vibraimage technology developers conducted series of studies on the relatively small patient sample (7 patients with a confirmed diagnosis of COVID-19, 5 males and 2 females, age 20–40 years, 110 videos), demonstrating the possibility of COVID-19 diagnosis during 5–20 seconds testing with more than 95% accuracy (Minkin, Akimov, 2022; Minkin, Kosenkov, 2021).

In this study, we show how to improve the accuracy of COVID-19 diagnosis on increased database of 324 videos (153 controls and 171 COVID-19 patients, including 107 control videos and 128 patient videos for AI learning and randomly selected 46 controls and 43 patients for testing) by increasing the amount of information obtained from video images. Patients with confirmed diagnosis of COVID-19 (5th wave omicron variant patients were added to alfa and delta variants base), who signed an informed consent and submitted video for processing, are Elsys Corp employees, St. Petersburg, Russia, age 20–73 years, 18 patients, 8 men and 10 females.

Head micromovements were measured in standard mode (Minkin et al., 2020) using a Microsoft LifeCam Studio webcam, resolution 640×480 pixels, connected to computers with Intel Core i7 processor. The distance between cameras and a head of the examined person sitting in front of the camera was 1 meter, the illumination of a subject (on a face of examined person) was at least 500 lux.

The duration of each video was 210 seconds. For the next processing and diagnostics were used video parts after 10th second from the start, since the first seconds after a person appearance in the frame have unstable BP. Figure 1 shows the location of a subject relative to the webcam located on the monitor during self-testing and video recording by Covid5s program interface, including the controlled position of the tested person on the monitor screen.

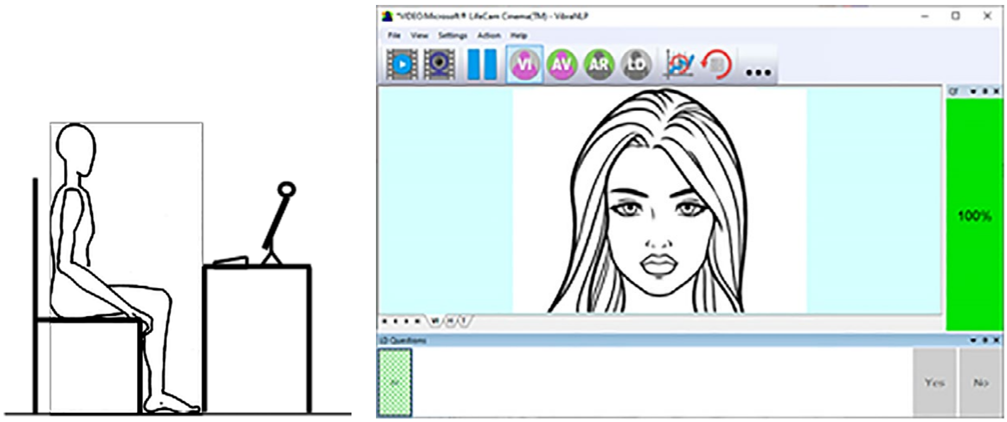

Fig. 1. Subject position during self-testing and video recording relative to the webcam and facial position on the monitor captured by Covid5s program

BP measurement and disease diagnosis were calculated at 10 Hz frequency, so each 200 second video contains approximately 2000 instant results of COVID-19 diagnosis. The total number of instant COVID-19 diagnostic results in the studied database of 252 videos included more than 500,000 values.

Results

Increasing the Number of Measured Behavioral Parameters

For a long time, were measured 40 BP (Akimov, Minkin, 2021) as the main dataset for COVID-19 diagnosis. However, the relatively poor diagnostic accuracy received by 40 BP algorithm on a new 252 videos database gave us the idea that increasing the number of BP leads to improving accuracy of COVID-19 diagnosis. Recall that 40 BP were taken from the standard BP package for classic psychophysiological testing (Minkin, 2020c). The standard set of 40 BP includes 12 main BP, supplemented with SD and variability (SD/M) for the analyzed time interval of 5-second. Thus, 12 BP turn into 36 BP values, to which 4 more main characteristics are added — the energy (E) and information (I) components, the current PPS value (Minkin, 2020b) and the total correlation (C) between BP (Minkin, 2020c). At the same time, the total number of parameters measured by the vibraimage system is much larger, and in addition to BP, vibraimage system calculates a number of parameters that were not supposed to be tied to the current PPS or BP. Additionally, the parameters of vibration amplitude, frequency, symmetry and vibraimage processing are measured (Minkin, 2007). To begin with, we decided to supplement the series of BP by parameters of amplitude (4 parameters) and frequency (5 parameters) of vibration, measured in parallel at different vibraimage settings N=2, 10, 25, their SD and variability. At this study 28 BP was added to past 40 BP, bringing the total to 68 BP. Naturally, we had to slightly change ANN structure used for training, increasing the input layer to 68 neurons equal to BP number. The structure of the linear feedforward three-layer ANN 68 × 20 × 1 used for AI training was detail described in previous studies (Minkin et al., 2020; Akimov, Minkin, 2021) and has not been changed in current research.

Figure 2 shows the dependence of testing database diagnosis accuracy A from training database discrimination accuracy D for ANN training variants of 40 and 68 BP, calculated on 324 video files database.

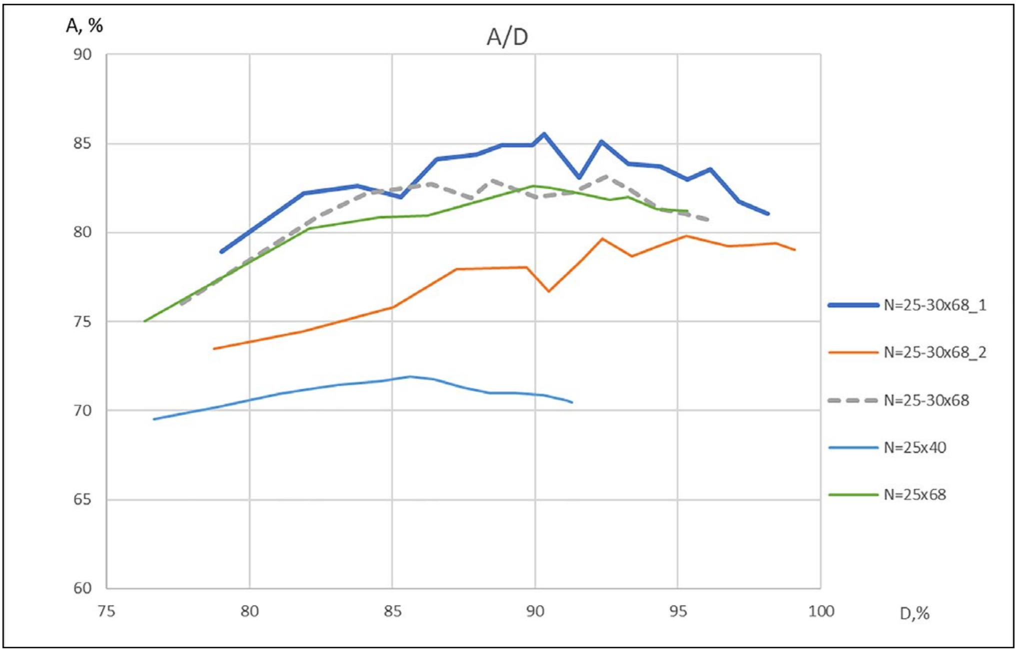

Fig. 2. *Dependence of COVID-19 diagnosis accuracy of testing database A from the discrimination accuracy D of training database for different ANN training variants for 40 and 68 BP.*

N = 25–30 × 68_1 — N = 25–30, measurement of 68 × 6 BP of the first disease stage;

N = 25–30 × 68_2 — N = 25–30, measurement of 68 × 6 BP of the second disease stage;

N = 25–30 × 68 — N = 25–30, measurement of 68 × 6 BP of the total disease;

N = 25 × 40 — N = 25, measurement of 40 BP of the total disease;

N = 25 × 68 — N = 25; measurement of 68 BP of the total disease

From Figure 2 follows that AI trained by N = 25 × 40 algorithm on a smaller database (Akimov, Minkin, 2021) runs parallel to the D axis (database discrimination during training), means that there is no increase in accuracy for testing on independent database. At the same time, adding BP data (algorithm N = 25 × 68 and others) during AI training makes it possible to increase the accuracy of the testing database diagnostics to values that are not inferior in accuracy to the results obtained on the basis of 110 video files (Minkin, Akimov, 2022).

The accuracy changes of COVID-19 diagnosis depending on diagnostic result averaging time obtained by BP number increasing from 40 to 68 is shown on Figure 3.

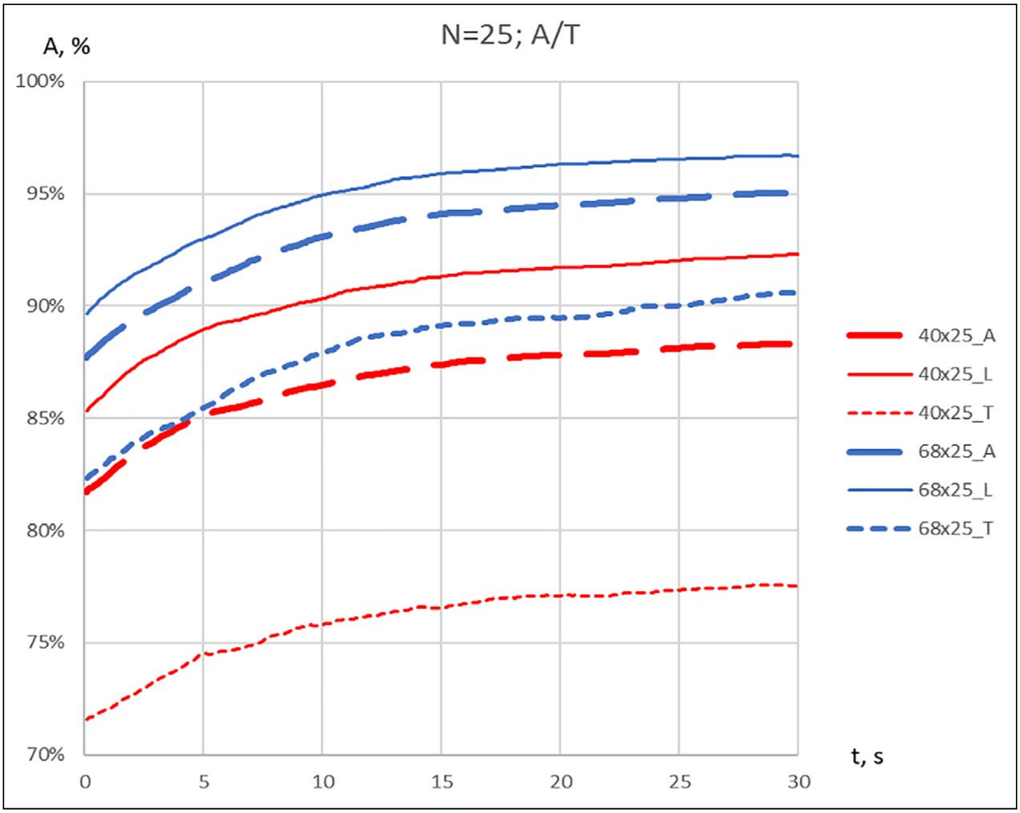

Fig. 3. *Accuracy of COVID-19 diagnostics based on 324 videos measuring 40 and 68 BP.*
40 × 25_A — diagnostic accuracy of the total database by 40 BP training;
40 × 25_L — base discrimination accuracy by 40 BP training;
40 × 25_T — accuracy of the testing base diagnostics by 40 BP training;
68 × 25_A — diagnostic accuracy of the total database by 68 BP training;
68 × 25_L — base discrimination accuracy by 68 BP training;
68 × 25_T — accuracy of the testing base diagnostics by 40 BP training

From figure 3 follows that the accuracy of COVID-19 diagnoses according to the test database (similar to the accuracy of random testing) during 20-second testing increased from 80% to 92% with an increase in the number of BP from 40 to 68 for AI training. The accuracy of diagnostics during 20-second testing on the full database increased from 92% to 98%, respectively, when moving from 40 BP to 68 BP.

Discretization Cloud. Replacing Specific Movement Discretization Interval to Row of Movement Discretization Intervals

In the classical applications of vibraimage technology for BP measuring is used fixed number of the interframe difference accumulation N, oriented to the period T = N/f of the physiological process, for example, N = 25; f = 5 Hz when studying responses to short 5-second stimuli (Minkin, 2021b) and testing time minimizing, for example, in the rapid diagnosis of early COVID-19 (Akimov, Minkin, 2021). At N = 50; f = 5Hz psychophysiological responses to comfortable 16-second stimuli were previously studied, and at N = 100; f = 5Hz, the free state of analyzed person (Minkin, 2020b). The choice of sampling frequency and analysis period was determined based on the Kotelnikov-Nyquist-Shannon theorem (Nyquist, 1928; Kotelnikov, 1933; Shannon, 1949), however the theorem provides an ideal case of analog signal shape reconstruction with infinite time of discrete analysis. On practice the time of micromovement analysis is always limited, and discretization of the movement process with a constant frequency or period of movement information accumulation has the ability to skip movement at any point in the image and at any time of measurement. Vibraimage transform of human head movement is mathematical function near to discrete Hartley transform (DHT) or discrete Fourier transform (DFT) so it could be named Discrete Vibraimage Transform (DVT) and Fast Vibraimage Transform (FVT) for real time operation. DVT differs from DHT and DFT by biological sense of vibraimage settings.

The accuracy of measuring the magnitude and frequency of movement (Minkin, 2019b) is a probability process depending on the following main factors — the magnitude of a movement, the optical contrast of moving object, the noise level of a camera, and object illumination. It was experimentally found by us that an increase in the number of close values of N (accumulation of the interframe difference) makes possible to increase the accuracy of movement measurement, and, consequently, the accuracy of diagnosing a disease. Of course, AI training on data array of discrete values N = 25, 26, 27, 28, 29, 30 takes about 6 times more time than on one value, since 6 times more BP is determined at each time point. If at N = 25, 68 BP are measured 10 times per second, then on blurred period 68 × 6 = 408 BP are also measured 10 times per second. However, AI training is carried out only once, and an increase in accuracy should occur with each subsequent diagnosis, if AI has learned to more correctly separate the signs of patients BP from control ones according to the blurred period of information accumulation.

Figure 4 compares the time dependence of COVID-19 diagnostics accuracy for one value of the interframe difference accumulation period N = 25 and for several values N = 25, 26, 27, 28, 29, 30.

Naturally, the curves 68 × 25_A; 68 × 25L; 68 × 25_T are identical in figures 3 and 4. The curves presented in figure 4 show a seemingly not so significant increase in diagnostic accuracy, “only” 1%, from 98% to 99% when comparing the results across the entire database (curves 68 × 25_A and 68 × 25–30_A). But 1% at such high accuracy values means a 50% reduction in errors, and a 50% reduction in error should certainly be fought for.

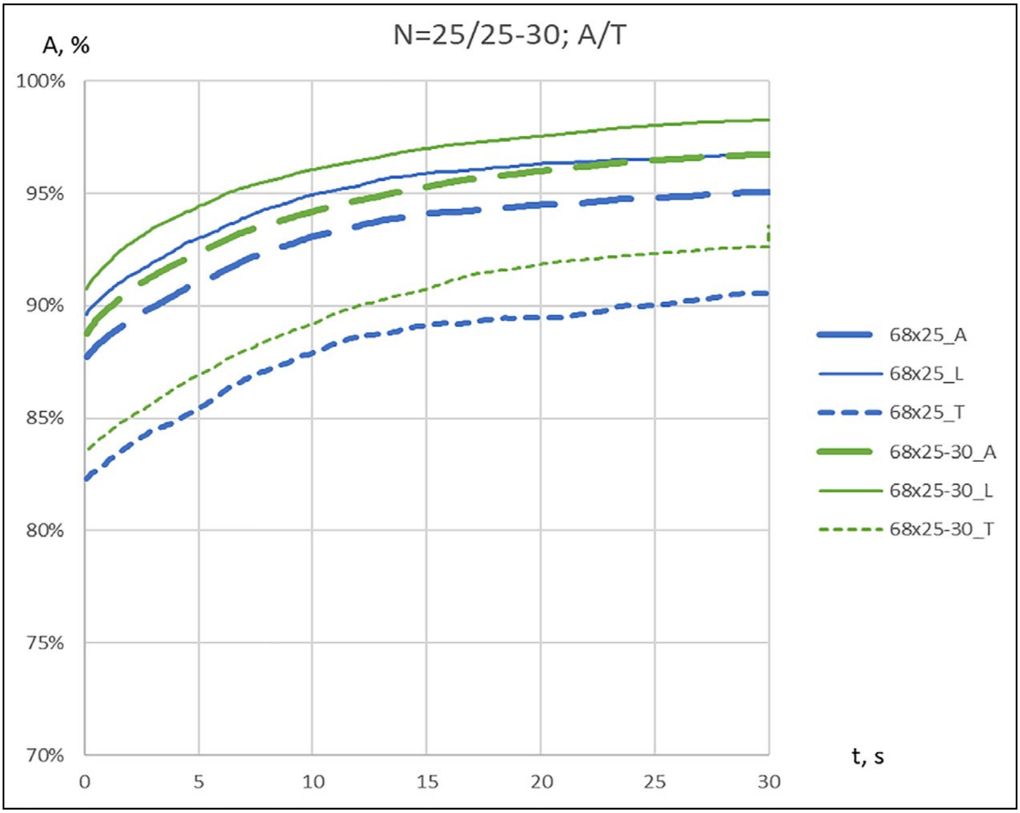

Fig. 4. *Time dependencies COVID-19 diagnostic accuracy for a fixed period of accumulation of interframe difference N = 25 and blurred period of the interframe difference accumulation N = 25–30.*

68 × 25_A — diagnostic accuracy of the total database with training at N = 25;
68 × 25_L — training base discrimination accuracy with training at N = 25;
68 × 25_T — accuracy of diagnostics of the test base at N = 25;
68 × 25–30_A — diagnostic accuracy of the total database with training at N = 25–30;
68 × 25–30_L — training base discrimination accuracy at N = 25–30;
68 × 25–30_T — accuracy of diagnostics of the test base at N = 25–30

AI training on single and separate groups. Formation of patient sample depending on the severity and/or the stage of a disease

Having video data of some patients throughout the entire period of the disease, we assumed that BP and symptoms of the patients should differ at different stages of the disease, primarily at the stage of the incubation period and the end of the disease (Khakimova, Khuzin, 2021). Such a difference in BP should presumably lead to a decrease in the accuracy of disease diagnosing if the videos of patients with different signs of the disease are combined into one total group for AI training. We hypothesized that the accuracy of diagnostics would increase if two separate groups of patients with COVID-19 were formed to train the AI, one from the videos of patients at an early stage of the disease and the other group of patients from the videos at a late stage of the disease. Training AI for a total group of patients should be more difficult, the accuracy of database discrimination when training AI, as well as the accuracy of recognition of a test group, should be somewhat lower than when training AI for separate groups with early and late signs of a disease.

However, at the same time, the question remained open: how to combine diagnostic results of AI training on separate data groups having two AI results? We assumed that the best option of AI training on separate databases would be to identify the disease by the maximum probability of disease (AI value) in any group. If the disease is just beginning, it detects by the first indicator, and if the disease ends, then by the second.

In this case, the sensitivity of the diagnostic method for each individual group can be only 50%, while the total sensitivity of the separate group method can reach 100%. Since the obtained diagnostic graphs for various AI training options turned out to be quite close, we present values of Accuracy, Sensitivity and Specificity for various options of forming AI training databases in Table 1. Note that method of AI training by different COVID-19 stage gives additional diagnostics information about current disease stage for tested patient.

Table 1

Accuracy characteristics of COVID-19 diagnostic for different AI training variants
(total database 1 and separate databases 1–2)

Accuracy characteristics / AI training variant	$\overline{\mathrm{R}}$	$\overline{\mathrm{AI}}$	$\overline{\mathrm{R'}}$
Total database 1 accuracy	98,46%	98,46%	98,46%
Total database 1 sensitivity	98,25%	98,25%	98,25%
Total database 1 specificity	98,69%	98,69%	98,69%
Total database 1 testing accuracy	96,63%	96,63%	96,63%
Separate databases 1–2 accuracy	98,77%	98,46%	98,46%
Separate databases 1–2 sensitivity	98,25%	98,25%	98,25%
Separate databases 1–2 specificity	99,35%	98,69%	98,69%
Separate databases 1–2 testing accuracy	96,63%	95,51%	95,51%

To increase the diagnostic accuracy assessment objectivity, we used 3 different diagnostic accuracy assessments $\overline{\mathrm{R}}$; $\overline{\mathrm{AI}}$; $\overline{\mathrm{R'}}$.

$\overline{\mathrm{R}} = {}^1/_n \sum \overline{\mathrm{R}_x}$ — average R value (instantaneous diagnostic values (0 or 1 in each file);

$\overline{\mathrm{AI}} = {}^1/_n \sum \overline{\mathrm{AI}_x}$ — mean significant AI (value from 0 to 1);

$\overline{\mathrm{R'}} = {}^1/_n \sum \overline{\mathrm{R'}_x}$ — mean value (diagnostic value 0 or 1 of the total file);

where:

n — number of files (252);

x — sample file from 1 to n;

i — single sample in the file along the time scale (10 samples per second);
$NN_{x,i}$ — instant AI value for file x, count i;
$AI_{x,i} = |E_x - 1 - NN_{x,i}|$ — AI confidence for file x, sample i;
E_x — expected AI for file x (1 or 0);
$R_{x,i} = AI_x > 0{,}5\ ?\ 1 : 0$ — diagnostic result by instant value for file x, count i (0 or 1);
$\overline{AI}_x$ — average AI for file x;
$\overline{R}_x$ — mean R value for file x, determined from instant values $R_{x,i}$;
$\overline{R'}_x = \overline{AI}_x > 0{,}5\ ?\ 1 : 0$ — diagnostic result by mean value for file x.

Table 1 results show close values of the accuracy COVID-19 diagnosis, for all used three indicators, option 1–2 (with training on separate bases, it has higher accuracy for instant estimation of diagnostic results (score , and option 1 (with training on total base) showed slightly better accuracy in estimating long time values of diagnostics (score $\overline{R'}$). It follows from Figure 4 that the instant diagnostic characteristics, which include $\overline{R}$; $\overline{AI}$ are lower than the time-averaged characteristics. The accuracy of COVID-19 diagnosing with a 5–20 second test should be between the values of $\overline{R}$; $\overline{AI}$ from the low border and the value of $\overline{R'}$ on the up border. In addition to Table 1, we present the distribution density of diagnosis results of a disease for different options for forming groups of patients 1 and 1–2 during AI training in Figure 5.

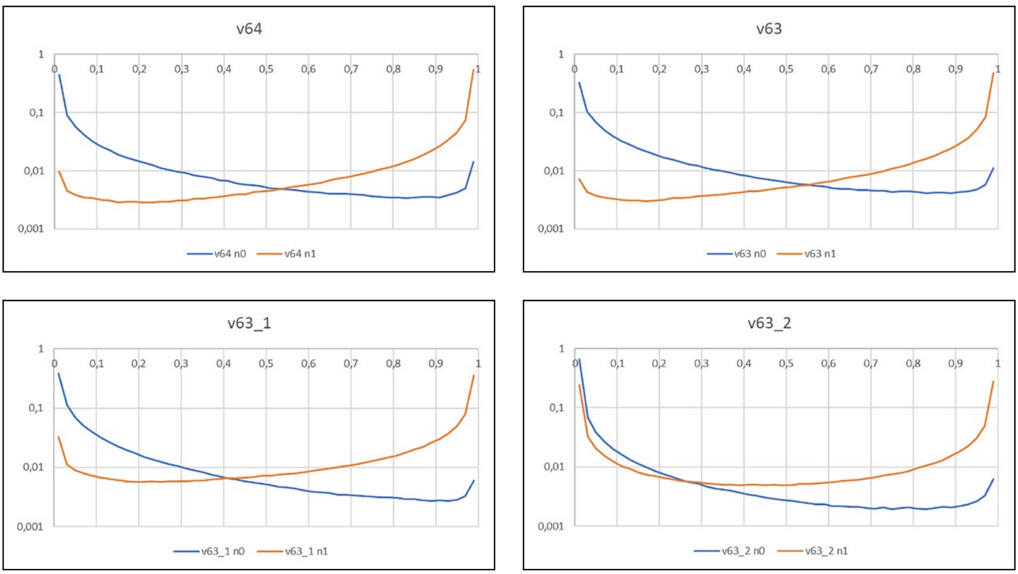

Fig. 5. *The distribution density of COVID-19 diagnosing results for different options of patient groups formation during AI training:*

V64 — total base for the formation of patient groups (0 — control group, 1 — patients with a confirmed diagnosis of COVID-19).

V63 — separate groups formation according to the disease stage.

V63_1 — density of diagnosis results on the early stage of the disease.

V63_2 — density of diagnosis results on the late stage of the disease

At first glance, the results shown in Figure 5 look strange. Particularly strange looks the density of diagnostics of the late stage of the disease V63_2, which shows shift crossing curves to left side. This is partly due to the fact that the number of patient videos in the late-stage disease database (31 training and 18 testing) is significantly inferior to the number of videos in the early-stage disease database (97 training and 25 testing), while the control database is the same for V63_1 and V63_2 database. However, this shows the advantage of the approach that gives the diagnostic result by the maximum AI value for each algorithm. In this case, becomes unimportant that one of the algorithms often shows an erroneous low value (false negative) for a larger number of patients at an early stage of a disease. The task of this second algorithm is to identify patients at a late stage of the disease and, judging by the diagnostic density given for V63, it does not cope with the task so badly, since the intersection point of the V63 plot for patients and controls is close enough to the border of the transition from healthy to sick with a diagnostic result value of 0.5.

The obtained results can be verified by readers, since the original digital data of the processed videos BP are posted on the public link https://psymaker.com/downloads/NN3.zip. The source BP data are given for row settings N = 25-30 obtained with a frequency of 10 Hz, so BP number is 6 times more than the number of instant diagnostic results.

Discussion

The presented results showed some examples of biometric information content increasing by video processing, although, of course, the possibilities of increasing biometric information content are not limited to the above principles. The source video, obtained with the frame rate 30 Hz in the 640 × 480 image format, from the point of view of information theory, is a digital data stream of 30 × 640 × 480 = 9.216 Mb/s with 8-bit coding of each image pixel. The standard vibraimage compresses streaming video to a stream of 40 BP, coming with a sampling rate of 5–10 Hz, i.e. only up to 200–400 bps. The compression ratio by DVT is at least 23040 times. Such significant compression allows processing AI information in real time and leaves room for reducing the compression ratio if the initial information is not enough to solve the problem. When solving exact problems, which include the diagnosis of COVID-19 by video image, in the presence of previously known results of medical diagnosis (RT-PCR, etc.), the main indicator of used method correctness is accuracy of test database processing. At the same time, vibraimage technology gives the possibility of obtaining additional information from the original video, which will lead to an increase in the accuracy of diagnostics. The increase or decrease in the accuracy of diagnostics is the criterion for the information content of additional data. For example, in addition to (or instead of) increasing the number of readings (row period), later possibly change the sampling frequency of movements (frequency cloud 5–6-7.5–10 Hz). Moreover, the amount of information contained in vibraimage can lead not to compression of the original video, but to an increase in its volume, since the interframe difference accumulated with a different sampling rate in each image element is an independent value, and the choice of accumulation periods is unlimited. The choice of frequencies and periods of movement sampling depends on the determined physiological processes, is of a probabilistic nature and is similar to the analysis of the signal-to-noise ratio in technical systems signal processing. The restriction to enter additional parameters is the high accuracy of database discrimination higher than 98%. After reaching such accuracy, entering additional parameters is inefficient, so the simplest method for further algorithm improving is training database increase. This can lead to a decrease in accuracy if the additional data in the database is noticeably different from the previous one. Precisely because we achieved a high diagnostic accuracy of 98% with the described parameters with the existing database size, we do not consider in this study other additional parameters that increase the diagnostic accuracy, although we predict their presence and effectiveness. Therefore, based on this study, we can formulate the fourth principle of vibraimage technology — **the principle of infinity**. If necessary, vibraimage technology allows extracting any amount of biometric information about a subject under study from a high-quality video image.

It should be noted that almost all data of patients with a confirmed diagnosis of COVID-19 in this study were obtained from patients with asymptomatic, mild or moderate disease. Moreover, the studied patients did not receive significant medical treatment, such as modern antibiotics. In our opinion, it should not be expected that the algorithm trained on patients with mild disease will show similar results for patients receiving serious drugs because it was known that drugs has influence to muscles microvibration (Rohracher, Inanaga, 1969). BP reflected by head micro-movements must also depend on other factors and AI trained to detect signs of a mild form of COVID-19 is not required to detect signs of a severe form of COVID-19, since it is not trained to do so. In our opinion, this does not at all reduce the practical value of the described method, since the main problem is precisely the early detection and diagnosis of COVID-19, and this is possible only for asymptomatic patients and patients with a mild form of the disease who do not receive powerful medical treatment, who do not know about their disease and are capable of infecting a significant number of others. Since COVID-19 is one of many viral infectious diseases, biologically and physically unremarkable, slightly different from other infectious diseases in severity (there are many infectious diseases with greater and lesser lethality) and the body's immune response, it is most likely that method of head micromovements analysis for COVID-19 diagnosing can be used for diagnosing other infectious and, possibly, non-infectious diseases. The physical or cybernetic model of a person (Minkin, 2017) considers any disease or pathology as a hindrance that affects the functioning of each physiological system. The vestibular system, with its main function of mechanical balance maintaining in the body, is highly sensitive and instantly reacts to any changes in the state of the body, including infectious influences. The development of templates showing the impact of an arbitrary disease on the normal functioning of the vestibular system is a purely technical matter, but certainly requires a huge amount of research BP set statistics for each disease.

In our opinion, the use of reflex movements and BP in modern medicine is very underestimated, although most doctors with significant practical experience make a preliminary diagnosis of a patient using an assessment of movements

(Rohracher, Inanaga, 1969; Bekhterev, 1999; O'Reilly, Plamondon, 2012; Khuzina, Mukhametzyanov, Bogdanov, 2008). An objective assessment of the reflex micro-movements of the human head (according to Bekhterev — objective psychology or reflexology) is exactly the addition that is necessary for modern evidence-based medicine, which is concentrated on local signs of the disease and does not take into account integral signs that depend on many feedbacks and constant self-regulation occurring in the human body (Novoseltsev, 1978). Despite the skepticism of modern medicine towards the use of BP for diseases diagnosing, a person is primarily a physical object and nature physical laws take precedence over modern medical concepts that require a clear establishment of specific biological signs of the diagnostic result. The increasing adoption of mathematical methods using AI in medicine (Patel et al., 2009; Gudigar et al., 2021; Wang et al., 2021; Cabitza, 2021) will inevitably change the existing approaches to diseases diagnosing, since AI always uses a huge volume aggregate data, and integral features are always more effective than local ones.

Biological behaviorism (O'Donohue, Kitchener, 1999) or reflexology (Bekhterev, 1999) including vibraimage technology, are independent and partially opposed to genetics direction of biology. However only the joint analysis of genetic, biochemical and behavioral processes occurring in a person allows to most fully characterize and explore PPS of a person, which is necessary for medical diagnosis. The exclusion of behavioral parameters from the diagnosis of diseases by modern evidence-based medicine leads to the current imbalance, when multiple symptoms of COVID-19 cannot be characterized by local genetic or biochemical parameters, since there is no complete picture inherent in a specific viral. Naturally, change in BP (head micromovements) occurs in patients with COVID-19 not only due to the presence of disease viruses, but for the most part it is a reaction to the response of the body's immune system to infection. In this regard, BP measuring by vibraimage technology can be used not only for early diagnosis of COVID-19, but also for conducting complex clinical studies at different stages of the disease and rehabilitation from COVID-19. Modern intolerance between genetics and behaviorism is a product of the 20th and 21st centuries, born from scientific wars and competition in scientific fields. Both sciences peacefully existed and complemented each other at the beginning of their development in the 19th century, for example, Mendel's genetic theory (Mendel, 1865) was actively combined with behavioral characteristics by his contemporaries Darwin (Darwin, 1872) and Galton (Galton, 1875).

Conclusion

The study showed almost limitless possibilities for increasing the information content of human head video processing in order to extract biometric information used to diagnose COVID-19 and/or other diseases. A video image of micromovements of a human head is no less informative for medical diagnostics than a biochemical blood test or a human genome, but understanding and scientific recognition of this fact cannot happen instantly. The inertia of human thinking and the conservatism of modern medicine hinders the practical implementation of modern information technologies in medicine. Currently, medicine allows AI use for training on traditional medical data (radiographs (Yousefzadeh et al., 2021), biochemical analysis data (Chieregato et al., 2021), but, unfortunately, is not ready to analyze the data of reflex micromovement and BP (Minkin et al., 2020). It was psychological obstacle that did not allow stopping the spread of the COVID-19 pandemic in 2 years using a non-contact method for diagnosing the disease by micromovements of the head using vibraimage technology and AI. However, traditions (even medical ones) change over time, this is inevitable process.

Another problematic point in the implementation of the proposed technology is the special ethical attitude in medicine to the video images of patients, which prevents the creation of open databases and the exchange of video data between interested parties. At the same time, in security technology and biometrics, this issue is resolved positively and the exchange of biometric data occurs, although with certain restrictions (Amelung, Machado, 2019), which do not stop the progress and development of biometric technologies.

Therefore, we are optimistic about the future of behavioral parameters using in medicine and believe that the method of diseases diagnosis based on the human head micromovement analysis using vibraimage technology and AI meets the requirements of modern evidence-based medicine and it will be used for diagnosing COVID-19 and other diseases.

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